AUTOMATIC GENERALIZATION OF SATELLITE- DERIVED 
LAND COVER INFORMATION

Thesis submitted for the degree of 
Doctor of Philosophy 
at the University of Leicester

by

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ABSTRACT

This thesis presents an original processing chain for automatic spatial and thematic generalization of satellite-derived products for introduction in a Geographic Information System.

The generalization process works on independent image-objects formed by a closed-boundary and a corresponding enclosed-region on the classified image. Initial image-objects are obtained by integrating the classified image with a geographically corresponding satellite-derived edge-segmented image.

The generalization process is organised in two main levels of abstraction. Firstly Geometric generalization, responsible for the spatial and thematic simplification of the classified image, elaborating the initial image-objects into higher-level polygons (the spatial basis of the final product).

Secondly Semantic generalization, responsible for the thematic conversion of the simplified product, associating each higher-level polygon to the most appropriate land use class.

The CORINE land cover classification scheme was taken as the target product during this thesis. This classification scheme is however overly detailed for direct comparison with satellite-derived products. To overcome this an intermediate classification was defined in this thesis: Pseudo CORINE (Pcor), which is a 1-level scheme containing: bottom-level CORINE classes which are automatically recognisable by image processing techniques, and 2nd-level CORINE classes as substitutes for those CORINE classes not automatically recognisable.

The definition of the Pcor scheme allowed an automatic nomenclature conversion, organised in two steps: 1) re-labelling, based on syntax matching, of low-level classes presenting a one-to-one relationship with a single Pcor class. 2) contextual reasoning, based on mutually exclusive hierarchical rules, for the conversion of low-level classes which present a one-to-many relationship with Pcor classes.

A fully automatic generalization process has been developed and verified during this work. The automatic generalization process has produced generalized products which are in excellent agreement with the target CORINE map. The simplification of geometry and content of the input information based on image-statistics and contextual rules is fully automatic, unsupervised, consistent, objective, repeatable and generally applicable.
To
Ryan, Ewan,
and
My GrandMother Silvia Maria
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I would like finally to acknowledge the European Commission for supporting my stay at the JRC Ispra.
CHAPTER 1
INTRODUCTION

Since the first observation satellite was launched over 20 years ago, remote sensing has gained great importance in the monitoring of the Earth’s surface. Remote sensing has for example been widely applied in providing digital data and information to support environmentalists making long term predictions of climatic and environmental changes at global scale.

The onboard satellite sensors record the variances in the electromagnetic spectrum of the energy coming from the Earth’s surface features as analogue signals and convert them into numeric values to form digital images, consisting of matrices of picture elements (pixels) each representing a particular ground area. Digital images may then be processed, classified and/or segmented, in order to convert spectral data to useful information.

Remotely sensed data have been successfully used in thematic mapping for some time. A thematic map is a specific-purpose map, containing information about a single theme, such as soil type, land use, sea surface temperature, statistical information etc. Remote sensing and thematic mapping is described in detail in chapter 2 of this thesis.

Classified images (thematic products) derived from satellite sources may not however, be directly used for general land-cover and land-use applications as they are usually too rich in spatial detail. These thematic products must be further processed before they may be directly used and combined with other digital data stored in a Geographic Information System (GIS) data base, as further described in chapter 2.

Since 1985 the European Commission has been supporting the CORINE programme. The main objective of this project is the creation of an information system to gather and organise information regarding the state of the environment and natural resources over the European territory. The CORINE system contains information on 22 different themes, such as general land cover, soil types, water resources, bathing water quality, coasts and settlements. The CORINE general land cover scheme, which was defined for manual mapping based on photo-interpretation, consists of a three level hierarchy of classes, with 44 classes in the lowest level. The majority of these 44 classes are so complex as to make impossible their recognition solely on the basis of spectral variances. Classes derived from remotely sensed images are usually
relatively straightforward (e.g. "urban", "water", "cereal crops") whereas classes used in
general land cover mapping (e.g. the CORINE nomenclature) are usually much more complex
(e.g. "land principally occupied by agriculture ...."), hence there is no direct one-to-one
correspondence between the image classes and the desired final map classes. As a
consequence of this it is impossible to directly compare classified satellite images with
CORINE maps, or in general with other land use schemes. The CORINE general land
cover nomenclature and the methodology of its derivation are introduced in chapter 2 and discussed
further in chapter 3. In order to emphasise the difference between the CORINE general land
cover nomenclature, which derives from photo-interpretation, and the land cover classification
derived from image processing, in this thesis the CORINE nomenclature will be referred to as
"land use".

The production of maps by photo-interpretation usually consists of several intermediate
visual interpretations and manipulations (cartographic operations), the application of which is
mostly subjective, and therefore unrepeatable, as highlighted in chapter 2. In practice map
updating is not practical if it has to be performed both frequently and manually. The use of
automatic digital image processing may provide more objective results and by following
regular rules prove to be useful in map updating.

The objective of this thesis is to automatically integrate thematic information, derived from
satellite-data classification, with CORINE land use maps and similar products. Experiments
on traditional raster filtering applied to classified images as a post-classification activity have
been performed during this thesis as an initial research study. A description of these
experiments and the results obtained is given in chapter 3.

In this thesis an original rule-based automatic processing chain for spatial and thematic
generalization of satellite-derived thematic products is presented. The role of generalization is
to match the level of abstraction in a classified image to the level of detail stored in GIS maps.
In addition the generalization must achieve a completely autonomous and automated
integration of satellite images with GIS and other spatial data. In chapter 4 the characteristics
of the automatic generalization process created for this research are described.

Cartographic generalization principles such as simplification, classification and induction
[Robinson et al, 1984], adapted to the image raster context, form the basis on which the whole
automatic generalization process developed for this thesis has been created. The
complementary interaction between remote sensing, GIS and cartography is discussed in chapter 2.

The automatic generalization process has been organised in two main levels of abstraction: low-level generalization, which is responsible for the spatial simplification of the input classified raster image, and high-level generalization, which is responsible for the thematic abstraction from the image classes to a more general land cover/land use nomenclature. The input for the generalization process consists of a classified raster image derived by image classification and a region edge map derived by image segmentation.

The generalization process works on independent image-objects, which consists of a closed boundary and a corresponding enclosed region. These input data must be integrated in order to derive image-objects information suitable for the generalization task. An automatic data integration process, considered as a necessary pre-generalization process, has been developed and is presented in chapter 5.

The low level generalization process, referred to as Geometric Generalization as described in chapter 6, performs the function of combining atomic regions, the boundaries of which are provided by the initial segmentation, to create the higher level polygons which will form the spatial basis of the final land cover map. Key processes for the low-level procedure are:

1. Extraction of spatial and spectral attributes from each atomic region;
2. Identification and elimination of erroneous sliver regions;
3. Rule-based atomic region merging to create the higher level land cover polygons; and
4. Spectral smoothing to create spectral class "patches" within each polygon which drive the higher level land cover assignment process.

The contextual simplification performed by the low-level generalization on the input classified image preserves the original spatial distribution of the input themes and the natural regional borders.

The high-level generalization procedure, referred to as Semantic Generalization and explained in chapter 7, works at a higher level of abstraction to automatically associate each of the image classes to the most appropriate CORINE class. The solution adopted to perform this association automatically, consists in the definition of a Pseudo CORINE (Pcor) land use nomenclature. The Pcor nomenclature contains all the CORINE land use classes judged to be uniquely recognisable by spectral and spatial image processing techniques, and contains the
CORINE parents of those classes considered being recognisable solely by photo-
interpretation. A parent of a CORINE class is one of the classes at the second level in the
CORINE hierarchy.

The high-level procedure consists of an expert system, which uses production rules to
assist the class-to-class/classes-to-class conversion within each polygon. A set of hierarchical
rules has been defined for each image class, in order to extract, dynamically during the expert
system reasoning, both local context and image-statistics for each low-level polygon to be
processed. A trace of the modifications made to the original classified image in producing the
final thematic map, is recorded by the generation of transitional raster products at the end of
each processing step.

The low-level generalization is fully automatic and objective in its performance. It may be
applied to any classified raster image independently of the themes occurring in the image. The
high level generalization has been implemented specifically for the CORINE land use
classification scheme, it presents, however an objective reasoning based on image-statistics
and contextual rules which are repeatable and generally applicable.

The performance of the automatic generalization process developed for this thesis shows
that a completely automatic and objective map-making processing chain can be realised
combining the complementary characteristics of thematic mapping from space and
cartography. Further, GIS provide the basis on which to organise a comprehensive integration
of the two disciplines. A full evaluation of the complete processing chain and a discussion
about the results obtained are given in chapter 8. In chapter 9 concluding remarks complete
the thesis.
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CHAPTER 2
REMOTE SENSING FOR LAND COVER/LAND USE APPLICATIONS

2.1 Introduction

In deriving information about the Earth's surface from remotely sensed data two processes are involved: 1) data acquisition and 2) data analysis.

The research described in this thesis is concerned with the conversion of satellite-derived thematic information into land cover information suitable for GIS input. In this chapter a brief introduction to satellite data collection, digital raw data pre-processing and image enhancement is given, prior to a more detailed description of the principles of data analysis (photo-interpretation, statistical and non-statistical digital image classification, and segmentation) which are the central topics for this research. A literature summary of relevant applications of image classification leading to the derivation of spatial information then follows. The complementary essence between remotely sensed data and GIS is also introduced in this chapter. Digital image generalization is highlighted at the end of the chapter as the means to convert the input thematic information into a format compatible with GIS maps.

2.2 Satellite Data Collection

Electromagnetic energy from the sun or an artificial source interacts with the Earth's surface in different ways; being reflected, absorbed and/or transmitted. This interaction modifies the intensity and spectral content of the reflected electromagnetic energy. An elementary scheme of the electromagnetic spectrum is shown in Fig. 2.1.

The visual effect of colour is an example of this interaction within the visible portion of the electromagnetic spectrum; grass absorbs the energy within the red and blue portions of the electromagnetic spectrum and reflects the energy within the green portion. This interaction is characteristic of the particular feature and is referred to as the spectral response.

Electromagnetic remote sensing of Earth's surface is based upon these principles of energy-material interaction. Satellite sensors measure and record the variation in the electromagnetic spectrum reflected from features on the Earth's surface (the spectral
response). Typical spectral response curves of grey bare soil, green vegetation and clear water are shown in Fig. 2.2.

A particular feature may vary its spectral response depending on temporal and spatial effects such as the time of the year chosen for monitoring cultivation (growing season or harvest season) and the geographic location of the cultivation (flat or inclined land). Furthermore the spectral response of a vegetation canopy (e.g. a forest) also depends on its state of health. The effective spectral response of a single feature is thus a set of spectral responses registered under different conditions and characteristics.

To take into account the entire spectral pattern information during image analysis, *multispectral* and *multitemporal* approaches are often used. A multispectral sensor has a number of channels, called *bands*, each recording radiation in specific parts of the spectrum simultaneously. Multitemporal sensing monitors the same spectral bands but at different times.

An important characteristic of satellite sensors is the *resolution* which helps to determine for which application the sensor is most suitable. There are four types of resolution: *spectral resolution* defined by the number and the width of bands (thus a high spectral resolution corresponds to a large number of narrow bands), *radiometric resolution* or sensitivity which is a measure of the smallest unit of ground reflectance that can be recorded by the sensor, *spatial resolution* which is a measure of the smallest area on the ground that the sensor is able to resolve, and *temporal resolution* which refers to how frequently imagery of a particular area may be obtained.

Satellite sensors collect analogue signals which must be converted (digitised) to form the *digital image*. A digital image consists of a matrix of picture elements, *pixels*, each representing a specific area on the ground. This digital image format may be conveniently processed in order to convert the spectral data into a more useful form, such as a land cover classification.
2.3 Land Use and Land Cover Mapping

Since the 1940's, aerial photographs have been used to map land use. With the advent of satellites, remotely sensed images have been used for land use and land cover mapping of large areas.

Land cover relates to the type of features present on the Earth's surface, while land use relates to the human activity or economic function associated with a specific piece of land (Lillesand and Kiefer, 1994). For example lakes, cereals and concrete are land cover types,
Remote sensing for Land Cover/Land Use Applications

while *urban areas, rural areas* and *industrial sites* are land use types. Land use types are composed of many land cover types e.g. an urban area consists of *roofs, roads, grass* etc.

Satellite images are particularly suitable for land cover mapping since (in general) there is a relationship between measured spectral response and the corresponding land cover type. It is inherently more difficult to discriminate land use types from satellite images. For example, a golf course has a spectral response similar to agricultural grassland used for grazing.

Land use and land cover types have been organised in hierarchical *classification systems* following their natural hierarchical relationship. The oldest classification system is that of the United States Geological Survey (USGS). The USGS land use/land cover system, which has been reviewed through the years to be consistent with the environmental changes, is organised in four levels, the first two of which are shown in Table 2.1.

<table>
<thead>
<tr>
<th>Level I</th>
<th>Level II</th>
</tr>
</thead>
<tbody>
<tr>
<td>1 Urban or built-up land</td>
<td>11 Residential</td>
</tr>
<tr>
<td></td>
<td>12 Commercial and service</td>
</tr>
<tr>
<td></td>
<td>13 Industrial</td>
</tr>
<tr>
<td></td>
<td>14 Transportation, communications, and utilities</td>
</tr>
<tr>
<td></td>
<td>15 Industrial and commercial complexes</td>
</tr>
<tr>
<td></td>
<td>16 Mixed urban or build-up land</td>
</tr>
<tr>
<td></td>
<td>17 Other urban or build-up land</td>
</tr>
<tr>
<td>2 Agricultural land</td>
<td>21 Cropland and pasture</td>
</tr>
<tr>
<td></td>
<td>22 Orchards, groves, vineyards, nurseries, and ornamental horticultural</td>
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<tr>
<td></td>
<td>areas</td>
</tr>
<tr>
<td></td>
<td>23 Confined feeding operations</td>
</tr>
<tr>
<td></td>
<td>24 Other agricultural land</td>
</tr>
<tr>
<td>3 Rangeland</td>
<td>31 Herbaceous rangeland</td>
</tr>
<tr>
<td></td>
<td>32 Shrub and brush rangeland</td>
</tr>
<tr>
<td></td>
<td>33 Mixed rangeland</td>
</tr>
<tr>
<td>4 Forest land</td>
<td>41 Deciduous forest land</td>
</tr>
<tr>
<td></td>
<td>42 Evergreen forest land</td>
</tr>
<tr>
<td></td>
<td>43 Mixed forest land</td>
</tr>
<tr>
<td>5 Water</td>
<td>51 Streams and canals</td>
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<tr>
<td></td>
<td>52 Lakes</td>
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<tr>
<td></td>
<td>53 Reservoirs</td>
</tr>
<tr>
<td></td>
<td>54 Bays and estuaries</td>
</tr>
<tr>
<td>6 Wetland</td>
<td>61 Forested wetland</td>
</tr>
<tr>
<td></td>
<td>62 Nonforested wetland</td>
</tr>
<tr>
<td>7 Barren land</td>
<td>71 Dry salt flats</td>
</tr>
<tr>
<td></td>
<td>72 Beaches</td>
</tr>
<tr>
<td></td>
<td>73 Sandy areas other than beaches</td>
</tr>
<tr>
<td></td>
<td>74 Bare exposed rock</td>
</tr>
<tr>
<td></td>
<td>75 Strip mines, quarries, and gravel pits</td>
</tr>
<tr>
<td></td>
<td>76 Transitional areas</td>
</tr>
<tr>
<td></td>
<td>77 Mixed barren land</td>
</tr>
<tr>
<td>8 Tundra</td>
<td>81 Shrub and brush tundra</td>
</tr>
<tr>
<td></td>
<td>82 Herbaceous tundra</td>
</tr>
<tr>
<td></td>
<td>83 Bare ground tundra</td>
</tr>
<tr>
<td></td>
<td>84 Wet tundra</td>
</tr>
<tr>
<td></td>
<td>85 Mixed tundra</td>
</tr>
<tr>
<td>9 Perennial snow or ice</td>
<td>91 Perennial snowfields</td>
</tr>
<tr>
<td></td>
<td>92 Glaciers</td>
</tr>
</tbody>
</table>

Table 2.1. USGS Land Use/Land Cover Classification Scheme.
Another important classification system is the CORINE general land use nomenclature developed by the European Commission (see introduction in chapter 1 and section 3.2), the structure of which is presented in Table 2.2.

<table>
<thead>
<tr>
<th>Level I</th>
<th>Level II</th>
<th>Level III</th>
</tr>
</thead>
<tbody>
<tr>
<td>Artificial Surfaces</td>
<td>11 Urban fabric</td>
<td>111 Continuous urban fabric</td>
</tr>
<tr>
<td></td>
<td>12 Industrial, commercial and</td>
<td>112 Discontinuous urban fabric</td>
</tr>
<tr>
<td></td>
<td>transport units</td>
<td>121 Industrial or commercial units</td>
</tr>
<tr>
<td></td>
<td></td>
<td>122 Road and rail networks and associated land</td>
</tr>
<tr>
<td></td>
<td></td>
<td>123 Port areas</td>
</tr>
<tr>
<td></td>
<td></td>
<td>124 Airports</td>
</tr>
<tr>
<td></td>
<td>13 Mine, dump and construction sites</td>
<td>131 Mineral extraction sites</td>
</tr>
<tr>
<td></td>
<td></td>
<td>132 Dump sites</td>
</tr>
<tr>
<td></td>
<td></td>
<td>133 Construction sites</td>
</tr>
<tr>
<td></td>
<td>14 Artificial, non-agricultural</td>
<td>141 Green urban areas</td>
</tr>
<tr>
<td></td>
<td>vegetation areas</td>
<td>142 Sport and leisure facilities</td>
</tr>
<tr>
<td></td>
<td></td>
<td>143 Industrial, commercial units</td>
</tr>
<tr>
<td></td>
<td>21 Arable land</td>
<td>211 Non-irrigated arable land</td>
</tr>
<tr>
<td></td>
<td>22 Permanent crops</td>
<td>212 Permanently irrigated land</td>
</tr>
<tr>
<td></td>
<td>23 Pastures</td>
<td>213 Rice fields</td>
</tr>
<tr>
<td></td>
<td>24 Heterogeneous agricultural areas</td>
<td>221 Vineyards</td>
</tr>
<tr>
<td></td>
<td></td>
<td>222 Fruit trees and berry plantations</td>
</tr>
<tr>
<td></td>
<td></td>
<td>223 Olive groves</td>
</tr>
<tr>
<td>Forest and semi-natural</td>
<td>31 Forest</td>
<td>231 Pastures</td>
</tr>
<tr>
<td>areas</td>
<td></td>
<td>241 Annual crops associated with permanent crops</td>
</tr>
<tr>
<td></td>
<td>32 Scrub and/or herbaceous</td>
<td>242 Complex cultivation patterns</td>
</tr>
<tr>
<td></td>
<td>vegetation associations</td>
<td>243 Land principally occupied by agriculture,</td>
</tr>
<tr>
<td></td>
<td></td>
<td>with significant areas of natural vegetation</td>
</tr>
<tr>
<td></td>
<td></td>
<td>244 Agro-forestry areas</td>
</tr>
<tr>
<td></td>
<td>33 Open space with little or no</td>
<td>311 Broad-leaved forest</td>
</tr>
<tr>
<td></td>
<td>vegetation</td>
<td>312 Coniferous forest</td>
</tr>
<tr>
<td></td>
<td></td>
<td>313 Mixed forest</td>
</tr>
<tr>
<td>Wetlands</td>
<td>41 Inland wetlands</td>
<td>321 Natural grassland</td>
</tr>
<tr>
<td></td>
<td>42 Maritime wetlands</td>
<td>322 Moors and heathland</td>
</tr>
<tr>
<td></td>
<td></td>
<td>323 Sclerophyllous vegetation</td>
</tr>
<tr>
<td></td>
<td></td>
<td>324 Transitional woodland-scrub</td>
</tr>
<tr>
<td></td>
<td></td>
<td>331 Beaches, dunes, sands</td>
</tr>
<tr>
<td></td>
<td></td>
<td>332 Bare rocks</td>
</tr>
<tr>
<td></td>
<td></td>
<td>333 Sparserly vegetated areas</td>
</tr>
<tr>
<td></td>
<td></td>
<td>334 Bunt areas</td>
</tr>
<tr>
<td></td>
<td></td>
<td>335 Glaciers and perpetual snow</td>
</tr>
<tr>
<td>Water bodies</td>
<td>51 Inland waters</td>
<td>411 Inland marshes</td>
</tr>
<tr>
<td></td>
<td>52 Marine waters</td>
<td>412 Peat bogs</td>
</tr>
<tr>
<td></td>
<td></td>
<td>421 Salt marshes</td>
</tr>
<tr>
<td></td>
<td></td>
<td>422 Salines</td>
</tr>
<tr>
<td></td>
<td></td>
<td>423 Intertidal flats</td>
</tr>
<tr>
<td></td>
<td></td>
<td>511 Water courses</td>
</tr>
<tr>
<td></td>
<td></td>
<td>512 Water bodies</td>
</tr>
<tr>
<td></td>
<td></td>
<td>521 Coastal lagoons</td>
</tr>
<tr>
<td></td>
<td></td>
<td>522 Estuaries</td>
</tr>
<tr>
<td></td>
<td></td>
<td>523 Sea and ocean</td>
</tr>
</tbody>
</table>

Table 2.2. CORINE Hierarchical Land Use Nomenclature [CORINE, 1989]

In general land use/land cover classification systems, used in the traditional map-making process, describe the landscape in a level of detail which it is impossible, in the majority of cases, to directly derive from digital remotely sensed images (photographs or satellite images).
The traditional process of map production, in fact, is based upon manual data manipulation and visual interpretation of aerial photographs and/or satellite images (photo-interpretation), in which the experience, the intuition, the imagination and the inductive capability of the interpreter are instinctively combined together for the extraction of information at a high level of abstraction. A typical CORINE land use map is shown in Fig. 2.3. Knowledge of the traditional map-making (photo-interpretation) process is necessary in order to follow the discussion presented in this thesis.
2.4 Elements of Photo-interpretation

Although photo-interpretation was not directly used in this thesis, it is the basis for the creation of traditional land use and land cover maps and was used as the sole basis of the CORINE land use project. The final output of the generalization process developed during this research is verified by comparison to CORINE maps. Therefore an understanding of photo-interpretation is necessary to assist the discussion presented in subsequent chapters. In this section a brief description of the principles of photo-interpretation is given. More detail on photographic systems, photo-interpretation equipment and applications on different soil types may be found in (Lillesand and Kiefer, 1994; Robinson et al., 1984; Campbell, 1993).

Photo-interpretation is the process by which a human interpreter extracts useful information from aerial photographs or satellite images. Principles and strategies to support the interpreter during this activity have been established, however success of the visual interpretation process depends upon the interpreter's knowledge of the subject under analysis, their experience, their capability of induction and their imagination.

As reported in Lillesand and Kiefer (1994) the elements guiding the photo-interpretation activity are: shape, size and spatial arrangement (pattern) of the objects to be identified, the colour or the brightness (tone) of the objects, the frequency of tonal change (texture), the occurrence of shadows, the geographic location of the real scene represented in the photograph (site) and the association, i.e. relationships among different objects logically associated with each other.

It is common practice during photo-interpretation to make an initial definition, on the photograph, of boundaries between areas of different types based on the guiding elements described above. The definition of a classification system and of the minimum mapping unit (MMU) are crucial for the successful completion of this activity. The classification system is a criteria used to logically separate different categories of features occurring in the photograph (see section 2.3). MMU is the size of the smallest area to be considered in the photograph and thus determines the level of detail of the interpretation.

Photo-interpreters normally use previously organised information about the objects or conditions to be identified in the photograph as a guide during the interpretation activity. This information is organised into interpretation keys:
• **Selective key**: the interpreter chooses, in a collection of previously interpreted photographs, the example which is most similar to the photographs under interpretation; in this way the interpretation is made by comparison.

• **Elimination key**: the interpreter excludes from the photograph the features not corresponding to specific characteristics or conditions. The objects surviving from the elimination procedure are (should be) the objects of interest to be mapped.

Although photo-interpretation is often subjective and limited by the human vision system, it cannot yet be completely substituted by digital image processing. The cartographer’s knowledge and experience may however be used during or after digital image processing, as will be highlighted in sections 2.6.2 and 2.8.

### 2.5 Principles of Digital Image Processing in Remote Sensing

Digital image processing in remote sensing is referred to as computer-assisted manipulation and interpretation of digital images in Lillesand and Kiefer (1994). However this is a simplistic description of a more complex collection of transformations applied to digital data to convert the input spectral values into useful information. Depending on the type of application, the information may then be represented in various formats: grey level image, thematic image, text description, statistics etc. The subdivision of digital image processing into three main categories of operations is generally accepted in the remote sensing community, these are: pre-processing, enhancement and classification.

**Pre-processing** concerns the correction of raw digital data. Physical and technical limitations of the detection system affect the measured signal during the data acquisition process, introducing distortions and noise in the recorded digital image. Raw digital data must therefore be corrected before any attempt is made to extract information. Details about the type of physical and technical disturbance, and about image correction techniques may be found in, among others, Lillesand and Kiefer (1994), Fraser and Kaufman (1985), Pearce (1985), Wrigley et al. (1984), Murphy et al. (1984).

**Image enhancement** operations are applied to the corrected raw image data, modifying the brightness value of each image pixel in order to increase the apparent distinction between different features in the scene. These operations improve visual interpretability and when
performed prior to image classification aid the automatic extraction of features (Lillesand and Kiefer, 1994; Curran, 1985).

*Image classification* operations are performed to interpret digital images by their numerical properties, transforming the spectral radiance into image classes. Image classification may be performed by referring (solely or in combination) to:

- Spectral characteristics carried by each pixel in order to associate one single theme to individual pixels or to groups of pixels;
- Spatial relationships among neighbouring pixels occurring systematically in the image, in order to identify objects by recognising their shape; and
- Variations of spectral and spatial characteristics occurring in the same area at different times.

More details on image classification may be found in Lillesand and Kiefer (1994) and Curran (1985). Since the products derived from these spectral pattern recognition techniques (a classification based solely on spectral characteristics of the image) are directly involved in this research the principles of the technique are presented in more detail in the following section.

### 2.5.1 Statistical Image Classification

The objective of image classification is to associate with each pixel of an image a land cover class (or *theme*) for this purpose decisions based on statistical rules are commonly used. Spectral pattern analysis may be performed in a supervised or unsupervised fashion.

*Supervised classification* is performed in two main steps: the training stage and the classification stage. During the *training stage* representative (training) areas are identified by the analyst directly on the image for each land cover theme to be classified in the image. The radiance properties of the pixels enclosed in a training area are used to statistically describe the class corresponding to that training area. These statistical descriptions are then used during the automatic classification stage to classify the entire image.

In general during the *classification stage* pixel values belonging to pixels in the training areas are graphically represented by plotting on a n-dimensional co-ordinate system, the *measurement space*. A measurement space is a system of orthogonal co-ordinates the number of which depend on the number *n* of the spectral image features. In a 2-channel image each
data pixel in the image has two digital values and the measurement space would be defined by the traditional 2-dimensional co-ordinate system (X,Y). The statistical representations described below are for this simple 2-dimensional measurement space. The two digital values associated with each pixel in the training sets are taken as (X,Y) co-ordinates and represented in the measurement space as shown in Fig. 2.4.a where each training pixel is labelled with the initial letter of the class it belongs to. Essentially, the classification consists in plotting each unknown image pixel in the measurement space and associating it to the class of the closest training area.

The concept of being closer may be modelled by several statistical strategies, such as:

1. **Minimum-distance-to-Means Classifier.** For each class portrayed in the measurement space the mean value for each band is also represented in the measurement space; the distance between the representation of an unknown pixel and the representation of the mean value of each class is calculated; the minimum distance determines the class the pixel belongs to, as shown in the diagram in Fig. 2.4.b. Ambiguities in the pixel-to-class association performed by the classifier may arise; in the diagram the points 1 and 2 are representations of two unknown pixels. For the pixel represented as 1, the class chosen by the classifier effectively corresponds to the class spatially closest to the point 1. The class chosen by the classifier for the pixel represented as 2 does not correspond to the spatially closest area to the point 2.

2. **Parallelepiped Classifier.** Ambiguous pixel-to-class association, as described for the minimum-distance-to-means classifier, may be solved defining decision regions in the measurement space. In the parallelepiped classifier, the smallest rectangular region (parallelepiped) surrounding the entire set of points representing each single training area is calculated and drawn in the measurement space. Representations of unknown pixels falling into a parallelepiped are associated with the class represented by that parallelepiped as shown in Fig. 2.4.c. Ambiguities may also arise with this strategy in the case of overlapping decision regions. More sophisticated calculations, however, may be applied to determine more precise decision regions.

3. **Gaussian Maximum Likelihood Classifier (MLC).** The MLC assumes that the graphic distribution of each training area in the measurement space is Gaussian (normally distributed) and the spectral patterns of each class may be described in terms of mean and covariance. The identity of each unknown pixel is calculated computing its statistical probability (the
likelihood) to belong to each class, and the highest probability determines the identity of the pixel. In the MLC the decision regions are graphically represented as ellipses as shown in Fig. 2.4.d.

The land cover types determined by unsupervised classification are also referred to as spectral classes. The unsupervised classification algorithms assume that spectral values within a given spectral class are spatially close when represented in the measurement space, and that different spectral classes appear spatially well separated when represented in the same measurement space. Essentially the unsupervised classification consists of representing each image pixel in the measurement space using as pixel co-ordinates the original spectral pixel values (spectral classes). The number of spectral classes in the image may be automatically calculated, and is not a priori determined by the analyst as in supervised classification.

Agglomerations of points, clusters, are generated in the measurement space; the number of clusters determines the number of spectral classes in the image. Each pixel in the image is then associated with a cluster, producing the classified image. Comparing the classified image with ground reference data (maps, pictures and other) the analyst determines the land cover type to associate with each cluster.
2.5.2. Non-Statistical Image Classification

One of the most discussed examples of non-statistical classifiers is the Artificial Neural Networks (ANN). Nodes in the artificial neural network have the capability of receiving, processing and transmitting the processed information to other nodes in a model of how the neurones may work in a human brain's communication system. ANN are used nowadays in a variety of applications where parallel processing is suitable and where phenomena under study cannot be modelled in a probabilistic manner (Bischof et al., 1992).
The Multilayered perceptron ANN model is the mostly used for spectral pattern recognition; it consists of a set of processing elements or nodes arranged in layers: input layer, one or more hidden layers and output layer. The nodes in successive layers are connected between each other by connections which carry weights. Fig. 2.5 shows a typical neural network classifier for multi-channel satellite data.

Fig. 2.5. Typical Multilayered Artificial Neural Network Classifier. Normally all nodes are fully connected with nodes in the layer(s) above and below.

Each node works independently receiving its input, computing simple arithmetical operations and passing its output to the nodes in the layer above. The ANN activity is very simple: the input is presented to the nodes at the input layer which transmits the input to the first hidden layer through the connections. Each node in any hidden layer 1) receives the weighted sum of all the outputs $o_i$ coming from the nodes at the layer below, $\sum_i w_{ij} o_i$, 2) calculates the value of the activation function $f$ on this input, $f(\sum_i w_{ij} o_i)$, and 3) transmits the result, the node output, to the layer above through the weighted connections. Calculations are propagated until the last (upper) hidden layer transmits the result to the nodes in the output layer.
The transformation performed by the activation function may vary depending on the type of application the network is used for. Usually two transformations are employed to produce the node output, the sigmoid and the hyperbolic tangent:

\[ o_j = \frac{1}{1+\exp(-\text{net}_j + \theta_j)} \]  \text{sigmoid transformation}

\[ o_j = m\tanh(k\text{net}_j) \]  \text{hyperbolic tangent transformation}

where \( \theta_j \), \( m \) and \( k \) are constants, and \( \text{net}_j = \sum_i w_{ij} o_i \)

The essential characteristic of an ANN model lies in its capability to 'learn' what it has to recognise. This learning activity is called \textit{training}, and it consists of an algorithm that iteratively calculates the weights to assign to the network connections. The process, by which the new weights are calculated, determines two different groups of ANN: unsupervised and supervised. For the \textit{unsupervised} ANN the training is made in order to emulate the distribution of the input data.

The \textit{supervised} ANN uses training data sets as defined for supervised statistical classification. During the training, a particular input (representing a particular known object) is presented to the input layer. The calculations are made and the network output is compared with the expected output for the given input. The weights are then adjusted in order to minimise the difference (the error) between the current output and the expected output with the generalized delta rule:

\[ \Delta w_{ji}(n+1) = \eta(\delta_j o_i) + \alpha \Delta w_{ji}(n) \]

where \( \Delta w_{ji}(n+1) \) is the change of a weight connecting nodes \( i \) and \( j \), in two successive layers, at the \( (n+1) \)th iteration, \( \delta_j \) is the rate of change of error with respect to the output from node \( j \), \( \eta \) is the learning rate and \( \alpha \) a momentum term (Kanellopoulos and Wilkinson, 1996). This kind of supervised learning action is called \textit{backpropagation}.

The ANN process stops, for both supervised and unsupervised models, when the error function has decreased to less than a threshold or when a fixed number of iterations has been reached.
Another example of non-statistical image processing is the use of *Expert Systems* (ES) during classification. ES are computer programs which manipulate symbolic knowledge and heuristics simulating the human expert in solving real problems. A generic ES, as described by Shea (1991) is usually organised in several components as shown in Fig. 2.6. The knowledge base consists of *declarative knowledge* which describes facts and concepts concerned with the field of application explaining *what* is the problem, and *procedural knowledge* which describes procedures and strategies to solve the problem, explaining *how* to use the declarative knowledge. The *inference engine* is the program which controls and directs the selection of the relevant rules, keeps tracks of the fired rules and controls rules execution.

The most common formalism for knowledge representation is the *production system* which generates rules (*production rules*) in a form which is easy to understand and to read. The syntax of a production rule is:

\[
\text{IF } \text{<antecedent>} \text{ THEN } \text{<consequent>}
\]

where *antecedent* and *consequent* are procedures performing actions on the pixels satisfying the rule. The execution of the rules can be driven by either the antecedent (*forward chaining*) or the consequent (*backward chaining*). Production rules can be integrated with declarative knowledge becoming *metarules*, which are used, for example, to determine conditions under which only some rules should be applied, excluding the others. This type of ES is also known as a *rule-based system*.

Satellite images, such as Landsat images, are as complex as the landscape they digitally represent. Land cover classes and their associated knowledge are naturally hierarchical, and a hierarchical classification approach is therefore appropriate for land cover applications (Ton *et al.*, 1991); rule-based systems may therefore be used for this purpose. Spectral and spatial knowledge about land cover types may be combined and organised in hierarchical rules to elaborate a more complex interpretation of the image.
2.5.3 Segmentation

An important activity commonly performed on digital image data for the extraction of spatial information is image segmentation. Segmentation collects those operations used in computer vision to decompose a pictorial image into meaningful parts, separating objects from the background and from other objects. Once separated each object is uniquely labelled. Segmentation techniques are generally applied in spectral pattern recognition to analyse digital image data before, during or after image classification. They are divided into three major groups: Clustering, Edge Detection and Region Extraction (Chang, 1989; Fu, 1982).

Clustering techniques assume that each class of region forms a distinct cluster in the multidimensional feature space. This is based on the same principle as statistical clustering.

Edge detection techniques assume that a boundary point (a pixel in the digital image) is represented in the image by a strong difference in pixel value between the boundary pixel and its surrounding pixels (the local context). The detection of edges is performed by applying local operators to each pixel in the image. The simplest form of local operators are the gradient operators such as the Roberts, Sobel and Prewitt operators which apply a gradient approximation function to each pixel in the image.
Considering the digital image as a discrete function \( f \) and the pixel value at the image co-ordinates \( x,y \) as the value of the function at those co-ordinates, \( f(x,y) \), thus the gradient of the digital image may be represented as in Fig. 2.7.

The Roberts, Sobel and Prewitt operators are based on the digital approximations and variations of the discrete gradient function produce a high magnitude where there is a strong variation in pixel value. These operators, based on moving windows of different sizes, are applied to each pixel in the image. The value of the central pixel in the window is calculated filling the gradient approximation function with the values of its neighbours in the window, as shown in Fig. 2.8.

**Region Extraction** techniques divide the images into regions rather than detecting regions boundaries; the _split and merge_ algorithm is a representative example. The Split and Merge algorithm works upon the fact that regions implicitly satisfy a homogeneity property. The image is divided into sub-images which are then split or merged if they satisfy a certain statistical uniformity criterion. Commonly the split method considers the whole image as the initial region to be split, and the merge method considers each pixel in the image as a separate region to be merged.

Combinations of different segmentation techniques are commonly used, taking advantage of the complementary characteristics of the different algorithms (Pavlidis and Liow, 1990) to refine the segmentation results (Le Moigne and Tilton, 1995). Knowledge derived from different sources, maps or previously segmented images, may be used in rule-based systems to facilitate the segmentation activity. The major objective of using knowledge-based segmentation systems is to increase the classification accuracy in images of the type used for environmental applications (Tailor _et al._, 1988).
The gradient function is: \[ \nabla f(x,y) = \frac{\partial f}{\partial x} + \frac{\partial f}{\partial y} \]

The magnitude of the gradient function is: \[ |\nabla f(x,y)| = \left(\left(\frac{\partial f}{\partial x}\right)^2 + \left(\frac{\partial f}{\partial y}\right)^2\right)^{\frac{1}{2}} \]

The directional angle is: \[ \theta = \arctan \frac{\partial f/\partial y}{\partial f/\partial x} \]

The approximate gradient function is: \[ \Delta x = f(x,y) - f(x-1,y) \quad \Delta y = f(x,y) - f(x,y-1) \]

represented by the local window operators:

\[
\begin{bmatrix}
-1 & 1 \\
-1 & 0 \\
0 & 1 \\
\end{bmatrix}
\]

Fig. 2.7. Approximation of the gradient function, magnitude and direction for the image discrete function \( f \).

\[
\begin{bmatrix}
0 & 1 \\
-1 & 0 \\
\end{bmatrix}
\quad \begin{bmatrix}
1 & 0 \\
0 & 1 \\
\end{bmatrix}
\quad |G| = |f(x,y) - f(x+1,y+1)| + |f(x+1,y) - f(x,y+1)|
\]

Roberts operator

\[
\begin{bmatrix}
-1 & -2 & -1 \\
0 & 0 & 0 \\
-1 & 2 & 1 \\
\end{bmatrix}
\quad \begin{bmatrix}
-1 & 0 & 1 \\
2 & 0 & 2 \\
0 & 0 & 1 \\
\end{bmatrix}
\quad G_x = (f(x+1,y-1) + 2f(x,y-1) + f(x+1,y-1)) - (f(x-1,y-1) + 2f(x-1,y-1) + f(x-1,y-1))
\quad G_y = (f(x+1,y-1) + 2f(x+1,y) + f(x+1,y+1)) - (f(x-1,y-1) + 2f(x-1,y) + f(x-1,y+1))
\]

Sobel operator

\[
\begin{bmatrix}
-1 & 0 & 1 \\
-1 & 0 & 1 \\
-1 & 0 & 1 \\
\end{bmatrix}
\quad \begin{bmatrix}
1 & 1 & 1 \\
0 & 0 & 0 \\
-1 & -1 & -1 \\
\end{bmatrix}
\quad G_x = (f(x+1,y-1) + f(x+1,y) + f(x+1,y+1)) - (f(x-1,y-1) + f(x-1,y) + f(x-1,y+1))
\quad G_y = (f(x+1,y-1) + f(x-1,y) + f(x+1,y-1)) - (f(x-1,y+1) + f(x+1,y-1) + f(x+1,y+1))
\]

Prewitt operator

Fig. 2.8. Roberts, Sobel and Prewitt edge operators and windows.
2.6 Applications of Digital Image Processing in Remote Sensing

The potential and more importantly the use of satellite-derived data during the activities of land-cover mapping, map-updating and environmental change detection is beginning to be accepted by the cartographic community (Robinson et al., 1984; Fuller et al., 1989; Fuller and Parsell, 1990; Wilkinson et al., 1993). However, the human expert is still required to guide the extraction of certain information from the images, as fully automated procedures are not always available or reliable. In the following sections a representative selection of literature concerning land cover mapping from digital remotely sensed data is presented.

2.6.1 Applications of Per-pixel Classification

Satellite-derived data have been successfully used in distinguishing between general land cover categories, such as “urban”, “rural”, “agricultural” or “grassland areas”, by extracting their spectral, spatial and temporal characteristics. Spatial pattern identification is commonly used during numerical classification of satellite images to distinguish well separated areas. For example urban areas (characterised by very small, close and regularly distributed features of concrete) can be distinguished from rural areas (characterised by larger and extended regions of vegetation with a low occurrence of concrete features). Roads may also be analysed by their spatial characteristics and associated with inner city areas or to peripheral areas by their density of connections.

Multi-temporal analysis and digital topographic data may be used to discriminate between crops types which have a similar spectral response. For example vineyards do not grow above a certain altitude and arable crops do not grow in winter time. Multi-temporal analysis takes advantage of how recurring crops change characteristics through the seasons, years, climatic variations and atmospheric conditions. This phenomenon is called phenology (Giardina, 1986). Narciso et al., 1992 collected information on crops in Italy, Spain and Greece, for the organisation of an agricultural information system for the European Communities, capable of providing reliable input data in agrometeorological models for crop state monitoring and yield forecasting. The introduction of remotely sensed information into the models was foreseen to improve the reliability of both input and output information. The system covers information such as classification of the crop types, crop requirements,
agriculture practices requirements, soil types, root and canopy structures, statistical and technical progress, phenological calendars and calendars of the agriculture practices.

Lo and Fung (1986) evaluated the usefulness of Landsat MSS data in land-use and land-cover mapping of large and spatially complex areas of China. They concluded that Landsat MSS is a convenient source of data (relatively cheap and fast) for monitoring large areas, but that its 80 m resolution is too coarse to satisfactorily discriminate spatially complex areas. In this context, training a supervised classification using information such as topographic aspects, slope, cropping systems etc. might be appropriate. Also a visual interpretation might be involved in determining the level of detail before running the digital analysis.

Kanellopoulos et al. (1992) used an artificial multi-layered neural network classifier on two-date multispectral SPOT HRV data to discriminate between 20 land-cover types. The size of the network and the sample size (98 nodes in the network and a ground data set of 1881 pixels) adversely affect the computing time of the training phase, though the accuracy of the final classification is high.

Buchan and Hubbard (1986) surveyed the structure of urban-fringe areas in SPOT images by a step-wise method including: 1) digital image enhancement, 2) general classification of urban and rural areas, 3) interactive classification (by the analyst) of more detailed fringe classes based on local knowledge. This study concluded that SPOT images are appropriate for general classifications but do not have sufficient spatial resolution (10m - 20m) for detailed inner city analysis. The analyst's local knowledge is therefore necessary.

Hvlaka (1987) calculated the edge density from Airborne Thematic Mapper (ATM) data (simulating Landsat Thematic Mapper (TM) imagery) to extract texture information in order to distinguish between rural and urban areas. The procedure consists of three steps: 1) edge enhancement by training techniques to maximise the difference between edge density measurements in urban and rural areas, 2) thresholding to create a binary image showing edge and non-edge pixels, and 3) derivation of local edge density by computation of proportions of edge pixels in a 31x31 filter moving on the edge/nonedge image. The local edge density was then used to classify the entire ATM image. The edge enhancement algorithm chosen for the first step of the procedure directly influences the overall success of the final classification, and the empirical choice of both the filter size and the threshold
makes the procedure unsuitable for automatic processing.

2.6.2 Per-field Image Analysis

Since the early 1980’s some remote sensing experts have adopted the per-field strategy in attempting to simulate the human vision system to improve classification results: objects are initially identified, recognised and then classified. As photo-interpreters combine different sources of information during photo-interpretation, structural (size and shape), contextual (pixels/regions interrelationships), topographic (height) and temporal information, attempts to improve per-pixel classification by combining data derived from different sources have also been made.

Mason et al. (1988) summarise several techniques derived from a literature review on using map information in order to extract useful information from images:

- The use of local texture information in the pixel neighbourhood during per-pixel classification;
- Segmentation of images into homogeneous regions subsequently classified as single entities;
- Segmentation of images supported by interactive intervention;
- The use of external information such as maps as complementary information before, during or after image classification;
- The use of map information to restrict the area of interest on the image, and to focus on what to look for; and
- The use of map data for training area(s) selection.

In these applications, however, the analyst interaction was necessary to consistently extract (and use) the information from the map.

Pedley and Curran (1991) developed a per-field classification associating each field in a SPOT HRV image with a single value calculated from in-field per-pixel statistics, they subsequently applied a per-field classification using a per-pixel classifier. The final product was presented as a GIS input. The initial field boundaries, visually extracted from a map and directly added to the image, represented the limit of this procedure.

Fuller (1992) described a semi-automated per-field analysis based on field cover type training, to map the land cover of Great Britain emphasising grassland cover types. Multi-
temporal (summer-winter) image analysis was used to distinguish permanent vegetation from seasonal crops, and deciduous vegetation from pastures. A supervised classification produced the cover-map and a knowledge-based system refined the cover-map using maps of coastal habitats to correct confusion between maritime and terrestrial cover-types. Masks of urban cover-types were used to cancel erroneous agricultural patches in towns etc. A final 3x3 raster filtering eliminated isolated pixels.

Weber (1994) used a supervised zonal approach for urban land cover classification as the basis for urban population estimation. Results derived from the per-zone analysis were compared to results derived from a per-pixel analysis. Multi-temporal SPOT images were integrated with digital census data and urban area outlines during both approaches. The comparison revealed similarities in the final products, but some classes (e.g. high-rise buildings) were better classified using the per-zone classification while others (e.g. industrial or commercial) were better classified using the per-pixel classification. They concluded that zonal analysis is appropriate in refining initial per-pixel classifications.

Knowledge of properties of form and feature compactness is important to discriminate and recognise different types of regions. Automatic image segmentation techniques have been applied to images characterised by small and regular fields (Ait Belaid et al., 1992), where a hierarchical region growing technique and cartographic data (field boundaries and crops locations) were used for the extraction and the classification of small agricultural fields. Mathematical morphology operations and smoothing techniques have been used by Parrot and Taud (1992) to detect circular structures within a SPOT image representing a volcanic area, where volcanic cones and explosion craters were clearly identifiable. Kusaka et al. (1990) integrated edge-detection and classification methods to classify SPOT images, initially extracting small spectrally homogeneous regions and classifying them by their spectral characteristics and spatial properties.

Unfortunately not all agricultural fields are spectrally homogeneous, small and regularly shaped. The landscape has so great a variety of aspects (geographic, structural and physical) that it is impossible to imagine and to model all of them in order to fix a general processing strategy.
2.6.3 Knowledge-based Image Analysis

Expert systems have been studied, developed and tested since the late 1970's in several applications for segmentation and classification of satellite images (Kontoes et al., 1993; Tailor et al., 1988; Nazif and Levine, 1984; Kanellopoulos et al., 1991; Ton et al., 1991; McKeown, 1987) and for image-map comparison or extraction of the Earth's resources information from satellite images (Goodenough et al., 1987; Fisher et al., 1988).

The structure of a general expert system, strategies for expert system development and methodologies for knowledge acquisition have been well defined (Plant, 1991; Batarekh et al., 1991; Hu and Rozenbilt, 1991). Knowledge acquisition, which is principally performed by knowledge engineers, is a time-consuming and expensive activity; thus the combination of artificial neural networks and expert systems, is now being studied to automate rule extraction and generation (Andrews and Geva, 1995; Fu, 1994; Towell and Shavlik, 1993).

Rule-based systems allow a control mechanism to activate, interactively, software programs according to a particular image structure or object configuration. One of the first rule-based systems to perform analysis of aerial photographs incorporating intrinsic properties of objects (shape, size, colour etc.) was presented by Nagao and Matsuyama, as reported in Mason et al. (1988). Intrinsic properties of objects may be used to uniquely recognise objects despite the spectral variances in the photograph.

Mason et al. (1988) developed a knowledge-based segmentation system combining several tools: 1) initial model-based segmentation generated by digital topographic maps, and 2) segmentation-by-recognition by iterative refinement of the initial segmentation using external knowledge embedded in a set of production rules and multi-temporal information. The digital segmentation map is used as low-level (initial) segmentation to be subsequently refined, or as a high-level model for classification. In both cases a reduction of occurrence of errors in the final products was noted when compared with the results obtained by traditional segmenters and per-pixel classifiers.

Møller-Jensen (1990) incorporated spatial and spectral information to create the knowledge for an expert system which was responsible for the classification of Landsat TM images covering urban areas. The method included: 1) edge detection for the extraction of linear structures typical in an urban area (roads, railways) which are then used to delimit the image segments, 2) feature extraction based on context, texture and spectral characteristics
for each segment, and 3) knowledge-based classification of each segment. Texture analysis, like object-shape-dependant analysis (2.6.2), depends on the specific urban areas under study, and therefore is not generally nor automatically applicable. Urban areas do not always contain similar spatial distribution of road connections, buildings aggregation, parks etc.

Kartikeyan et al. (1995) developed a rule-based system for land cover classification from satellite images, taking advantage of both visual interpretation and spectral image classification techniques. The classification problem was considered as a set of hypotheses to verify (true or false) by means of the iterative inference mechanism of the expert system. The parallelepiped approach for classification (section 2.5.1), also used in visual interpretation, was adopted to specify the knowledge-base on spectral features: each rule in an hypothesis specified a parallelepiped in the feature space. An evidential reasoning approach was employed to evaluate each hypothesis. Accurate ground data (measurements and/or observations concerning the areas under analysis) was used to train the expert system, this represents the major limit of the application. Confusion occurring in the final classification was clarified separately through expert intervention using non-spectral information (shape, size, texture and pattern).

2.7 Derivation of Spatial Information

Together with paper maps and ground surveys, remote sensing represents an important source of spatial information. It is the common opinion for the map-making community that strategies to extract information from satellite images are not adequate despite the fact that the satellite sensor technology and the computer technology (hardware and software) has improved considerably since the first satellite was launched 20 years ago.

The crucial point is that satellite-derived thematic products (even if obtained by sophisticated, consistent, contextual and combined image processing techniques, as described in the previous section) are still produced on a pixel-basis and thus they represent a "poor" cartographic form of data representation when compared to photo-interpreted products which show discrete spatial entities. One also has to consider the risk of an uncontrolled combination of spectral, spatial and contextual knowledge during image processing which may lead to redundant and confused information rather than clarification. This section focuses on the fundamental task of understanding what kind of information can really be extracted
from remotely sensed data and what is its relationship with the information presented in traditional maps.

The difference between the satellite-derived and traditional map information arises primarily from how the Earth's surface is represented in remotely sensed data and in maps. Products derived from image processing present in detail the composition of the landscape, dividing it in adjacent squares and small regions (the pixels). No context or spatial knowledge is implicit in the image subdivision, even although the matrix represents a practical means for automatic analysis and for directly correlating geographic locations on the ground. The minimum mapping size for the satellite data is thus the pixel, which may vary in size (20x20m, 30x30m, 80x80m etc.) depending on the satellite sensor and on the application, but still represents an "anonymous" and independent rectangular area on the ground. Spectral characteristics generally show a simple one-to-one correspondence with land cover classes, such as "grass", "concrete", "asphalt", "building", "roads", "water", "coniferous" etc.

Traditional maps represent more generally the utilisation of the landscape; the cartographer initially interprets the scene and then divides it on the map emphasising the most significant regional boundaries. Unwanted detail is thus eliminated making clear to the user the information which is portrayed in the map. In traditional maps each entity is associated with a land use type such as "high density urban", "low density urban", "sport facilities", "industrial site" etc. none of which is a single cover-type. On the contrary, a land use class may be seen as a "variable" combination of different land cover types. The minimum mapping unit for land-use mapping is much larger than the pixel size, unless, for example, NOAA AVHRR data is used (EC, 1996).

The classified remotely sensed image must still be interpreted to represent consistent information, while the map is the final result of an interpretation activity (Burrough, 1986). Land cover and land use mapping may then be seen as representations of the reality at two different levels of abstraction, respectively low-level and high-level, therefore, their products cannot be directly compared.

Attempts to extract information at a higher level of abstraction from classified images have used various strategies, both automated and semi-automated (Barr and Barnsley, 1995):

- **Convolution kernel method**, based on a kernel window moving along the raster image, to associate land use from the frequency and spatial arrangement of land cover classes
occurring in the window. These algorithms (taken from image enhancement techniques) are easy to implement but present several limits, for example the empirical definition of the window size, the association of land use, based on local information, they do not take into account the global image aspects nor the entities occurring in the image, they also have difficulty in analysing morphological aspects like shape and containment;

- **Contextual classification**, which examines together with the spectral properties of a given pixel also its relationship with neighbouring pixels and the entire image context. These classifiers may be however computationally intensive and are dependant on the specific task; and

- **GIS-guided spatial analysis**. Classified images are imported in vector format into GIS in the form of thematic maps and then processed by GIS tools.

An alternative and representative approach for consistent spatial information extraction is presented in Barnsley et al. (1993) for monitoring urban land use from satellite sensor images. To overcome the limits of the previously mentioned post-classification techniques, particularly the effects of local kernel windows applications, and in order to define a common, intermediate level of abstraction between low level and high level land information, the authors present an **object-based spatial re-classification** procedure. Basically the spatial re-classification technique consists of two steps: 1) a traditional per-pixel land cover classification is initially performed, and 2) a subsequent spatial post-classification is applied to the classified image to extract land use information. The term object denotes a region of uniform land cover within the image. The image is then analysed as containing a number of discrete objects, which may be recognised by their shape, size, location and context.

The object-based spatial re-classification consists of an interactive process guided by the user through a specific interface developed for querying applications. The queries are based on specific definitions of urban areas. Specific data structures and models are necessary to allow the interactive and independent abstraction and the encoding of the information relating to each object in the image. Therefore, urban-rural boundaries of the studied area have been manually digitised from the 1:25000-scale Ordnance Survey maps, and the definitions of urban areas taken from the standard Office of Population Censuses and Statistics definitions. The data structure used to support the query activity was an extension of the Region Adjacency Graph (RAG) (Nichol, 1990) to represent image objects and their
properties. The promising results obtained by this technique are due to the choice and the combination of appropriate model and data structures.

To adapt the analysis approach of photo-interpretation to the analysis of satellite images it is necessary to modify the representation of image-objects and the representation of a priori knowledge about the real scene. In this context Barr and Barnsley (1995) summarise these needs as follows:

- Techniques to perform low-level image segmentation or classification (extract principal objects);
- Techniques to identify image objects and to encode their geometrical description (boundaries representation);
- Techniques to process the geometrical description of image-objects; deriving information on morphological properties and spatial relationships;
- A scheme to encode and store the information derived from each image object;
- Techniques to locate and analyse groups of objects with specified spatial relationships or other specified object properties; and
- A control mechanism to order and execute the above techniques in a manner consistent with the task of interpretation.

2.7.1 Remotely Sensed data and Geographic Information Systems

The demand for spatial information continues to grow and satellite sensors represent a fast source of data compared to traditional map-making and aerial photo-interpretation.

Geographical Information Systems (GIS) have an important role in the successful creation of a map. Burrough (1986) defines GIS as the "... the marriage between remote sensing ... and cartography...". There is general agreement that GIS is more than just a tool for geographic and spatial data base management, nor only a tool for automated-cartography and it is not only a set of procedures to manipulate and introduce remotely sensed data into the map-making process. GIS performs all of this and more and should be considered as an independent discipline. Remote sensing and GIS technologies are complementary to each other in several ways (Wilkinson et al., 1993):

- Remote sensing can provide regularly updated data sets for GIS;
- GIS data sets can be used during image processing to increase classification accuracy; and
• GIS and satellite data, once integrated, can be successfully used for environmental monitoring, analysis, modelling and decision-making.

Fisher and Lindenberg (1989) present a "three-way interaction model..." among remote sensing, cartography and GIS in which none of the disciplines is predominant (Fig. 2.9).

The map is an abstract model of reality and represents a medium for the comprehension, the record and the communication of spatial relationships and forms (Cassettari, 1993). As a communication medium the information represented in the map has been derived using cartographic generalization and design. Unwin (1986) outlines two main limits in spatial analysis, described below:

1. While organising and manipulating data in order to emphasise the "selected" information, other information is irreversibly destroyed; the manual manipulation of data guided by the cartographer expert is in fact not repeatable (by another cartographer or by the same one at another time) being based upon intuition and subjectivity (which are not quantifiable); and
2. The lack of geographical precision in the majority of maps when real objects are generalized into nominal categories (for example an areal object generalized into a point object).

The use of GIS for spatial analysis requires accurate spatial location, therefore, in this context, cartography and GIS tools are not compatible. Satellite images and image processing techniques may be used to compensate the gap between map information and GIS data requirements, providing strategies to transform data in a reversible manner and, with raster
analysis, to keep trace of the geographical relationship of the generalized object and its real position on the ground.

The efficiency of remote sensing and GIS data integration during both image processing and computer-aided map-making has been widely demonstrated. Pedley (1986) combines, for example, remotely sensed data and digital map data during image interpretation and image analysis. Mason et al. (1988) use digital maps during segmentation and classification of satellite images to increase the image processing accuracy, prior to introduction into a GIS.

Fosnight (1992) refers to the statistical information stored in GIS as the input information during the definition of a geographical resource model, i.e. the collection of information such as slope, soil, land-use and land-cover. Jensen et al. (1990) have used remote sensing and GIS technology to assist oil-spills monitoring and managing. Mattikally (1994) applied an integrated GIS approach, based upon mathematical concepts of Sets and Groups, to overlay classification images and digital maps for land cover change assessment. Treitz et al. (1992) applied GIS integrated techniques for land-cover and land-use mapping at the rural-urban fringe. Öberg and Andersson (1993) used information derived from SPOT satellite imagery and ARC/INFO utilities to assess and monitor environmental damage from mining activities. GRS (1992) reports success in using Landsat TM derived data and GIS analysis in mapping over 12 million acres of land.

Today it is possible to obtain digital versions of maps derived from satellite imagery to introduce in GIS, but this activity cannot yet be called integration. Visual inspection and direct manual correction are still extensively performed during the map-making process even if executed in a completely digital environment (Trotter, 1991).

Despite the attempts made to achieve an automated scheme of classification, several technical problems continue to present a barrier for operational GIS/remote sensing data integration, (McKeown, 1987; Faust et al., 1991; Lunetta et al., 1991; Dobson, 1993; Congalton, 1991; Fisher, 1994), such as:
1. Error propagation during image processing;
2. Positional or categorical errors;
3. Pixels versus polygons as different geographical space representation; and
Ehlers et al. (1989) pointed out that the raster-vector dichotomy is only apparent and valid at a low level of abstraction, in the attempt to process digital images by cartographic tools in a GIS environment, for subsequent direct comparison with digital maps data. Once again the problems of creating an operational integration of remotely sensed data with digital maps in a GIS environment concerns the erroneous desire to establish a direct correspondence between information represented at different levels of detail and abstraction, as described in section 2.6.

In conclusion classified images still have to be heavily processed, taking into account context, spectral and spatial characteristics and other morphological properties for a more consistent spatial unit (larger than the pixel) before reaching a higher (or at least an intermediate) level of abstraction for operational integration with traditional map data in digital format. The map-making process is complex; it combines cartographer's intuition and imagination, but also quantifiable experience and rigorous methodology in selecting the entities to be portrayed in the final map. These aspects are part of cartographic and statistical generalization, a crucial point to the aim of this thesis to match the quantitative and qualitative abstraction of the information represented in classified images. In the following section, principles and objectives of cartographic generalization are summarised with particular emphasis on conceptual models for generalization in a digital environment.

2.8 Digital Map Generalization

The mental generalization process by which the cartographer interprets images (combining subjective intuition, imagination, experience, and objective knowledge) is essential in cartography not only to help in understanding, but also because the scaled representation of reality is the essence of the map-making process. Generalization helps to remove unwanted detail when changes in scale occur and to eliminate unnecessary detail for thematic mapping (Armstrong, 1991). In manual cartography, the cartographer decides when and how to apply the generalization processes depending on certain constraints, called controls, which are the objectives and the scale of the map, the graphic limits of the system employed (or the capabilities of the reader) and the quality of the data to be mapped.

The discipline of digital generalization may be defined as the attempt to provide consistency of application and independent application of the generalization manipulations by
following sequential computer instructions (McMaster and Shea, 1992). Digital Generalization may be cartographic, when operators are applied to the input data in order to compensate the visual aesthetic qualities of a scale change, and statistical, when operating within the data base to smooth or simplify its content.

Cartographic generalization includes several operations which Robinson et al. (1984) group in four categories:

- **Simplification**: the selection of the characteristics to be reported in the final map is a simplification of the representation of the original scene with the reduction of unnecessary detail and the enhancement of important information;

- **Classification**: ordering and grouping of similar data into categories;

- **Symbolisation**: the graphic representation on the final map of the important classified characteristics; and

- **Induction**: the logical (geographical) process of extending the information contained in the map.

McMaster (1991) describes conceptual models for digital generalization proposed in the last 20 years, in the attempt to understand, and encode, the complex generalization process. The major difficulty in digital generalization is incorporating the cartographer's intuition and experience into a computing algorithm. Objective experience may be organised in objective knowledge, and expert systems may support the consistent application of the generalization manipulations (operators). However, the expert intuition still remains the unknown in the map making process.

Armstrong (1991) classifies three kinds of knowledge necessary for a generalization expert system: 1) geometrical knowledge: the set of feature descriptions including absolute and relative locations, and other feature aspects important for the generalization. This is fundamental for point or line simplification, and useful during the application of the classification operator; 2) structural knowledge: organises the expertise in the geographical phenomena, for example, hydrology, geomorphology etc., important for grouping similar data into categories during the classification; and 3) procedural knowledge: to aid in the selection of the most suitable generalization operator.

Brassel and Weibel (1988) presented a conceptual model for digital generalization based upon five processes as shown in Fig. 2.10.
- **Structure recognition** identifies specific cartographic objects, spatial relations and measures of importance;
- **Process recognition** identifies the appropriate generalization operator to apply to the geographical scene, and prepares data and parameters;
- **Process modelling** is consequent to the process recognition step and compiles rules and procedures;
- **Process execution** performs the effective automated generalization, in which rules are applied to the original data base creating the generalized output; and
- **Data Display** performs the vectorization or rasterization of the output data into the target map.

McMaster and Shea (1992) propose a conceptual model, illustrated in Fig. 2.11, based upon three fundamental questions: *why*, *how* and *when* to generalize:
The Philosophical Objectives component answers the question why to perform digital generalization considering the specific requirements of the problem and the digital environment limits simulating the cartographers intuition and expertise.

The Cartometric Evaluation component answers the question when to generalize. The definition of an automatic control process for the selection of the generalization operators and the order of application is a difficult task, involving geometric properties and perceptual motivations. The selection of the operators depends on the importance of the individual features, their complexity and the complexity of the entire scene. Although this is not part of the effective generalization it is a fundamental component (Mackaness, 1991).

The Spatial and Attribute Transformations component answers the question how to generalize, and then performs the transformation of the input into generalized data. Spatial operators perform the geographical generalization (in raster and vector environment) modifying the geographic characteristics of the input data. The attribute transformations are responsible for the statistical generalization modifying the attributes of the input data and thus altering the original statistical characteristics.

McMaster and Monmonier (1989) describe four kinds of raster-mode generalization, in contrast to the vector-mode operation (Fig. 2.11) which are:

- Structural Generalization which involves spatial re-arrangement of the raster matrix such as reduction in the matrix size or raster-vector-raster conversion;
- Numerical Generalization which includes operators such as low-pass filters (smoothing operator) and high-pass filters (edge-enhancement operator);
- Numerical Classification, commonly called image classification; and
- Categorical Generalization which employs further generalization, at a nominal level, of maps and classified images by merging, aggregation and attribute-change operators.
### Digital Generalization

**Philosophical Objectives** *(Why to generalize)*
- reducing complexity
- maintaining spatial accuracy
- maintaining attribute accuracy
- maintaining aesthetic quality
- maintaining a logical hierarchy
- consistently applying generalization rules

**Theoretical Elements**

**Geometric Conditions**
- congestion
- coalescence
- conflict
- complication
- inconsistency
- imperceptibility

**Application-Specific Elements**
- map purpose and intended audience
- appropriateness of scale
- retention of clarity

**Computational Elements**
- cost effective algorithms
- maximum data reduction
- minimum memory/disk requirements

**Spatial and Holistic Measures**
- density measures
- distribution measures
- length and proximity measures
- shape measures
- distance measures
- Gestalt measures
- abstract measures

**Transformation Controls**
- generalization operator selection
- algorithm selection
- parameter selection

**Cartometric Evaluation** *(When to generalize)*

**Spatial Transformation**
- Vector-mode Operators
  - simplification
  - smoothing
  - aggregation
  - amalgamation
  - merging
  - collapse
  - refinement
  - exaggeration
  - enhancement
  - displacement

- Raster-mode Operators
  - Structural Generalization
  - numerical generalization
  - resampling
  - numerical categorisation
  - merging (of categories)

**Attribute Transformation**
- classification
- symbolisation

Fig. 2.11. Digital Generalization Model by [McMaster and Shea, 1992]. Raster-mode operations [McMaster and Monmonier, 1989] are shown in the spatial transformations component.

#### 2.8.1 Applications of Digital Generalization

A considerable amount has been published on the topic of automatic generalization, however little of this can be considered fully automatic. Confusion in using terms such as automated, automatic, semi-automatic is common in the literature. To understand the following section one should remember the definition of *automatic process* which in the context of this thesis means a process working in complete autonomy from the user.

Schylberg (1993) presents a computational method for generalization of cartographic data (in a raster environment) in which rules guide spatial transformations, such as amalgamation, simplification and deletion, under user supervision. A hierarchical order of importance among classes is used during the application of the amalgamation and simplification operators, with the result that the order of importance is highly influential on the final map appearance.
In the recent literature two pilot studies have documented the automation of the CORINE land use map production. The British Institute of Terrestrial Ecology (ITE) has conducted a pilot study described by Fuller and Brown (1994) to develop a GIS based interactive generalization process to convert the ITE land cover map of Great Britain into a CORINE format. ARC/INFO commands have been used to perform the conversion (therefore automated conversion) interactively activated and tested by the expert user.

The Finnish Geodetic Institute conducted a similar study to convert an existing land use database of Finland to a CORINE land use standard database (Jaakkola, 1994). Land use and forest classification (SLAM) and the Finnish building register maps were overlaid on a supervised classification of a satellite image. This was taken as the initial regions partition on which aggregation of point features, amalgamation of small areal features and smoothing of border lines were applied. During the execution of these spatial operators, direct conversion of input classes into CORINE classes was made. Amalgamation and aggregation operators were applied following a pre-defined order of importance among input classes.

2.9 Summary

To date, satellite images have been used during map-making activities mainly as auxiliary data in photo-interpretation, in a few cases they have been processed semi-automatically, requiring, however, analyst interaction and supervision to obtain a product compatible to the end user requirements.

Satellite data in land use mapping has to date been mis-used, in many cases, forgetting (or ignoring) the basic distinction between land use and land cover. As described in the preceding sections various complex techniques have been applied directly to raw satellite data in order to extract land use information in an attempt to either simulate the photo-interpreter activity, or to use refining procedures on per-pixel classified images to obtain a product similar to photo-interpreted maps.

This has led to the erroneous application of techniques created for different levels of detail extraction than that to which they were applied. For example:

1. Object-shape and texture dependant algorithms applied to raw spectral images are neither automatic nor do they produce consistent or repeatable results; and
2. Filtering techniques based on moving windows, the size of which is decided empirically, do not guarantee reliable results.

It is fundamental to the generalization process to understand the relationship between the information derived from satellite images and the information presented in a map. Land cover information is a low level (basic) description of the (more general) high level land use information. The manual map-making process teaches us to acquire the best photograph of the real scene, observe the detail, extract the detail important for the final map, analyse it (involving data manipulation and map entities definition) and finally associate a category to each map entity.

The essence of a satellite image is its subdivision in pixels, each of which has associated a digital number representing the spectral response of the feature on the Earth's surface which it represents. Therefore per-pixel classifications are the most appropriate techniques for the extraction of information which respect the image characteristics. It is at a subsequent level of processing that characteristics, such as the distribution of themes in the image, texture, context etc., should be observed, analysed and categorised.

Digital generalization operations are appropriate to process classified images. However, up to now, these kind of operations have failed because analysts impose (during the analysis) constraints in what they want to observe in the image, and constraints on what they believe is important.

For a fully consistent and automatic process it is essential to allow the image to guide the generalization process using with fidelity the information contained within it. This will thus avoid the need for expert interaction. Excluding the expert interaction during the automatic application of a process does not mean excluding the expert from the process. The generalization of classified images requires a step-wise procedure to convert from the basic low level data to a higher level of information. Rule-based systems are appropriate for this type of step-wise approach, particularly when the rules may be organised in a hierarchically and mutually exclusive manner. The role of the expert therefore is essential in defining the number of steps, the type of information to extract from the image at each step, and the definition of the objective, and generally applicable rules.
2.10 Thesis Objectives

In this thesis an automatic generalization process for classified images is presented. Algorithms, performing spatial and thematic simplification, and a classification system conversion, autonomously process the input classified image at two levels of detail abstraction. Key components of the process are:

1. Geometric generalization created to exploit the spectral characteristics and the natural themes distribution of the input data to reduce detail; and
2. Semantic generalization to perform the conversion from land cover to land use information.

The automatic generalization process developed for this thesis uses original tools and automatic techniques to:

- Extract principal image-objects from low level satellite-derived products (segmentation and per-pixel classification);
- Encode the geometrical description (the boundaries) of the principal image-objects;
- Process the image-objects geometrical description to derive and store object attributes;
- Process image-objects and objects attributes to determine main mapping entities;
- Dynamically update and store new attributes and geometrical descriptions for modified entities; and
- Convert from the input low level classification system to the target high level map classification system for direct GIS input.

The generalization process, written in the C language and running on a DECstation 5000/240 Digital Equipment, is guided by a rule-based mechanism which autonomously executes the techniques listed above. The rules contain simple and objective constraints. The rule-based approach allows fully automatic processing by consistent (repeatable) application of simplification and smoothing operators, using per-object image processing while ignoring the object-shape dependency. The expert system organised for the nomenclature conversion although created specifically for the CORINE land use classification scheme, presents an objective reasoning based on image-statistics and contextual rules which are repeatable and generally applicable.
CHAPTER 3 EXPLORING CURRENT GENERALIZATION METHODS and an ALTERNATIVE

3.1 Satellite data and processing for an automatic step-wise data conversion

3.2 The land use/land cover nomenclature problem

3.2.1 The one-to-many classes relationship

3.3 Post-classification Process

3.3.1 Tests on subimage1

3.3.2 Tests on subimage2

3.4 From Per-pixel Filtering towards an Automatic Per-region Smoothing

3.5 The Automatic Per-region Post-classification Process

3.6 Automatic Derivation of Spatial Information from Satellite Images
CHAPTER 3
EXPLORING CURRENT GENERALIZATION METHODS and an ALTERNATIVE

3.1 Satellite data and processing for an automatic step-wise data conversion

As highlighted in section 2.7.1, the map-making process needs data provided at regular intervals in order to produce up-to-date products representing the landscape for modern land cover applications, and the traditional map-making process based on manual generalization is not sufficient to cover the increasing demand of spatial information.

In chapter 2 we established that the use of satellite images provides a constant source of geographic data, however it has also been explained that a direct conversion of the land cover information extracted from satellite images into more general information to use in the map-making process is still not possible. Attempts made in the past for the direct conversion of classified images into "generalized" land use maps (section 2.6) are not semantically correct, considering the distinct level of abstraction between land cover and land use information as explained in section 2.7. The proof of this is the necessity of expert interaction, supervision and interpretation in using raw satellite images or classified images for map-making purposes.

The simulation of cartographic activities in automated processing has recently become an independent discipline, digital generalization (see section 2.8) which is applied directly to satellite images and classifications (amongst other spatial data) to enable the extraction of spatial information and incorporation into GIS data bases. A considerable amount has been published on the topic of automatic generalization, however little of this can be considered fully automatic. Confusion in using terms such as automated, automatic and semi-automatic is common in the literature. To understand the following sections the definition of automatic process in the context of this thesis should be recalled: a process working in complete autonomy from the user.

In this chapter the problem of the land use/land cover nomenclature conversion are discussed as one of the main impediments for an automatic conversion of land cover classified images into land use map. Iterative Majority Filtering (Guo and Moore, 1991; Goldberg et al., 1975) which is the most commonly used filtering algorithm (section 2.7) as the base for the post-classification of classified images in order to provide a simplified representation of land cover information, are examined in this chapter in terms of practical
use in an automatic process. Experiments performed are also reported to support the conclusions stated in the last section of this chapter.

3.2 The land use/land cover nomenclature problem

The main problem in design and development of an automatic process to convert land cover images into land use maps, or to convert land cover/land use maps from one classification system to another, derives primarily from the map (land use/land cover) nomenclature which, in general, has been defined for photo-interpretation. For example the CORINE land use data base produces digital maps which give a realistic representation of the land cover varieties of Europe (CORINE, 1991), based on manual interpretation.

The CORINE land cover map uses a 3-level hierarchical classification scheme with 44 classes at the bottom (CORINE, 1989), see Table 2.2. One of the major difficulties in updating CORINE maps is that the classes in the nomenclature are intended to be obtained from aerial and/or satellite imagery by photo-interpretation. CORINE land use maps only contain parcels exceeding 25 hectares which means that all cartographic detail is generalized to this level making it very difficult to compare it with data coming from different sources. Revising these maps every 5-10 years is essential to take into account changes in the landscape through anthropogenic or natural processes, however this procedure is too time-consuming for regular revisions and is also subject to difficulties of reproducibility.

Studies have been conducted on the detection of CORINE land cover classes from satellite data to automatically (or semi-automatically) update CORINE maps Wilkinson and Folving, (1991) and Wilkinson et al., (1992). From these studies it was concluded that a large number of the 44 CORINE land cover classes cannot be easily detected from satellite images by traditional image processing, mainly because either the definitions of these classes are too vague or they are a mixture of surface conditions only interpretable by the human expert. Examples are the classes such as sport facilities or construction sites which are too fine in detail to be detected by automatic image processing, and agricultural classes which are a mixture of different spectral types.

Automatic comparisons between data extracted from a CORINE map representing Lisbon Bay in Portugal and from a geographically corresponding classified image have been made for this research, in order to verify the relationship between each CORINE polygon in
the map and combinations of land cover classes on the classified image. The CORINE map polygons in ARC/INFO data base and the DIG files corresponding to their geometrical description have been read by a program written to automatically overlay each polygon onto the classified image. For each polygon in the map a list of the land cover classes occurring within its perimeter was then organised. Results of this comparison are described in the following section.

3.2.1 The one-to-many classes relationship

The section of the CORINE map (shown in Fig. 2.3) was overlaid onto a 16-classes classification obtained by an Artificial Neural Network classifier (section 2.5.2), Fig. 3.1, from the Landsat TM image illustrated in Fig. 3.2. For each CORINE polygon occurring in the CORINE map a list of image classes occurring in the polygon area, together with other statistical information, such as the number of occurrences in polygons for each image class and the percentages of the occupied polygon area, were automatically extracted.

An example of the statistical information is given below. In the entire Lisbon Bay CORINE map there were 27 polygons for the class 1.1.1 Continuous Urban Fabric and for 6 of these the corresponding statistics are shown in the Tables 3.1 and 3.2.

Among the six polygons only the polygon no. 4 is consistent to the "city" context containing a large percentage of tiled-concrete and a low percentage of natural grassland; however, doubts may arise from the 9% occurrence of agricultural land. The polygon number 6 might be representative of a park site in a city with the 78% of grassland and weeds, 18% of concrete which maybe pedestrian paths or public buildings, and 3% of water which maybe artificial ponds or water courses. However, these suggestions are no more than hypotheses which are too vague to be used as knowledge for an automatic land type recognition.
Fig. 3.1. Classified image of Lisbon Bay (Portugal) 16-classes.
Fig. 3.2. Landsat Thematic Mapper image of Lisbon Bay (Portugal) (colour composite of channels 4, 5 and 3). [original satellite ©ESA 1991, distributed by Eurimage].
Table 3.1. Statistics associated with 4 CORINE polygons corresponding with land use class 1.1.1 Continuous Urban Fabric. The name of the image class occurring in the polygon and the percentage of the polygon area occupied by the class are shown.
Exploring Current Generalization Methods and an Alternative

Table 3.2. Statistics associated with 2 CORINE polygons corresponding to the land use class 1.1.1 Continuous Urban Fabric. The name of the image class occurring in the polygon and the percentage of the polygon area occupied by the class are shown.

From Tables 3.1 and 3.2, ranges of values representing the lower and the upper percentage of occupied polygon area of each image class, were extracted and are presented in Table 3.3:

Table 3.3. Minimum and maximum percentage range of CORINE polygon’s area occupied by the 16 spectral classes when overlaying the classified image to the corresponding section of the CORINE polygons map.
Tables 3.1, 3.2 and 3.3 show considerable ambiguity but they do correspond to what human experience and common opinion describes as a “continuous urban fabric”. Analysing the content of each polygon reveals that practically every polygon contains occurrences of all image classes in different percentages, this is obviously related to the CORINE polygon size being overlain onto a thematically very detailed area, which do not allow the definition of a “standard” range of percentages consistent to every CORINE polygon. This leads to the conclusion that the parcels of 25 hectares are too large and not suitable for automatic conversion of per-pixel image classifications. The 25 hectares minimum mapping size is contradictory compared with the detail of the CORINE nomenclature. In general one would expect the use of a few broad classes to describe large spatial units, and the use of more specific classes to describe small spatial units, similarly to the detail which may be recognised in photographs taken at a distance, compared with the detail in photographs taken very close to the subject. The CORINE classification system does not respect these principles.

The choice of an intermediate mapping size, for example 10 hectares, to fill the gap between per-pixel satellite-derived products and CORINE maps is not sufficient however on its own, for a straightforward data-to-map conversion. The abstraction from a per-pixel representation, through a per-entity representation (polygon, region, field etc.) up to the final map, requires a step-wise generalization process.

3.3 Post-classification Process

To date, attempts to directly generalize classified images by applying cartographic generalization operators failed to be automatic because of the semantic difference between the classified image and the target map. The nomenclature of diverse map classes and minimum mapping sizes require expert interaction in selecting the generalization operator, and determining the conditions in which to apply it, as seen in the previous section. The derivation of more general information from land cover images must necessarily be a step-wise process which sequentially and consistently elevates the abstraction level of the initial information to a product showing land use information.

Post-classification algorithms using traditional filtering based on moving windows (convolution kernel methods, section 2.7) are very popular for their computing simplicity combined with their strong smoothing power. For this thesis, Iterative Majority Filtering
(IMF) (Guo and Moore, 1991; Goldberg et al., 1975) has been chosen for testing of the performance of per-pixel filtering techniques on classified images, in order to establish the effective and practical use of their performances in automatic algorithms. IMF is one of the most commonly used per-pixel filtering technique, and it is the base on which more sophisticated methods have been developed. From the analysis of the IMF performance, general conclusions on the characteristics of per-pixel filtering techniques may be derived.

As a post-classification process, IMF is generally applied to eliminate isolated pixels and it is based upon the use of a 3x3 filter. For each pixel IMF calculates the most frequently occurring class (majority) in the pixel neighbourhood. The central pixel of the neighbourhood is then re-assigned to the majority class. The filter is applied to each pixel in the image until no further changes occur. The choice of the filter size is usually case-dependent and experimentally tested directly on the image.

IMF yields a very homogeneous product, but as previously stated its iterative and uncontrolled execution causes the loss of important spatial information such as the displacement of an original border or the inconsistent redistribution of important themes in the image. To overcome this negative effect Wilkinson (1993) has created an algorithm, Iterative Reduced Class Growing (IRCG), which balances the effects produced by the filtering on the image (the elimination of information) re-introducing the information “judged” quantitatively important.

In the IRCG context the term class population indicates the number of pixels belonging to an image class occurring on the classified image. After IMF the image aspect changes, accompanied by a modification of the population of each image class. An image class is defined as being under-populated if its population has been reduced by IMF. An image class is defined as being over-populated if its population has been increased by IMF. To determine if a theme has been significantly reduced or increased, a percentage threshold (user-defined) is used during the IRCG application. Only image classes for which the difference between the original and filtered population (or between one iteration and the subsequent) is greater than the threshold are re-introduced in the image.

IRCG uses a moving window filter in an iterative performance as does IMF; the filter is applied to each pixel in the image, and both central pixel and local neighbourhood are examined. At the beginning of the processing and after each iteration, the IRCG procedure
calculates percentages and statistics for each image class population. IRCG checks if the central pixel belongs to a reduced image class; if so the neighbouring pixels within the filter are also examined. Any neighbour belonging to an over-populated image class is re-assigned to the central pixel image class. The process stops when no more changes occur in the images or when a number (user-defined) of iterations is reached.

IMF and IRCG have been combined to perform some tests on per-pixel filtering and are reported in the following sections. Two 256x256 pixels (lines and columns) sections of the Lisbon Bay classified image, Fig. 3.3, were chosen for the experiments. The two image sections are referred to as subimage1 and subimage2. In the following sections of this chapter the series of tests are applied to the two sub-image sections and a discussion of the results obtained is presented.
Fig. 3.3. Classified image of Lisbon Bay (Portugal). 10-classes image classification of the Landsat TM image of Lisbon Bay obtained from an Artificial Neural Network Classifier [Kanellopoulos, 1992]
3.3.1 Tests on subimage1

IMF was initially applied to the subimage1, shown in Fig. 3.4, using a 3x3 filter. As shown in Fig. 3.5 subimage1 has been smoothed but it is still far from being a suitable GIS input: too fine detail still occurs. The input distribution of image classes in subimage1 (many agglomerations of few pixels close to each other) is such that IMF did not reduce sufficiently the detail nor enhance sufficiently the information.

IRCG was then applied to the filtered product with a 3x3 filter. As expected IRCG did not affect the image class populations as shown in Fig. 3.6. The reason for this is that the original and the filtered theme populations were balanced and none of the image class populations satisfied the imposed threshold on population variation.

IMF was then applied to the original subimage1 with a larger filter, 5x5, in order to create larger homogeneous regions. Again IRCG was applied immediately after IMF using the same 5x5 filter; the result is shown in Fig. 3.7. From a visual inspection it is clear that the use of a larger filter does not increase the information, on the contrary it produces (pictorial) confusion erroneously modifying the natural spatial distribution of regions. The filtered product in fact has been distorted in its appearance: pixel distributions assumed the shape of the filter, which could not be corrected by a subsequent filtering with a smaller filter, as shown in Fig. 3.8.

Subimage1 has been demonstrated to be drastically affected by the per-pixel filtering but, because of its spatial characteristics, IMF could not reduce the detail nor enhance the information satisfactorily from the cartographic point of view, emphasising the dependency of the filtering performance from the original image characteristics.
Fig. 3.4. Subimage1. A 256x256 section of the entire classified image of Lisbon Bay shown in Fig. 3.3. This image section has been used for experiments on per-pixel filtering.
Fig. 3.5. Filtered image obtained by the application of IMF 3x3 on Subimage1.
Fig. 3.6. Filtered image obtained by the application of IRCG 3x3 on the product shown in Fig. 3.5.
Fig. 3.7. Filtered image obtained by the sequential application of IMF 5x5 and IRCG 5x5 on Subimage1.
Fig. 3.8. Filtered image obtained by the application of IMF 3x3 on the product shown in Fig. 3.7.
3.3.2 Tests on subimage2

A different image section, subimage2 shown in Fig. 3.9, with different spatial characteristics, has been used for similar smoothing tests. From visual observation, subimage2 presents larger natural regions characterised by a noisy appearance. A water course (a section of the river Tejo) is present; small agricultural fields with regular shape, typical in Mediterranean regions, are also shown. However the image section is very noisy in its appearance.

Considering the type of disturbance occurring in subimage2 (isolated pixels and isolated groups of 2-3 pixels) a 3x3 filter has been chosen to initially smooth the scene. IMF was thus applied, and the filtered image is shown in Fig. 3.10 with results being highly smoothed. IRCG was then applied to the smoothed image but no relevant changes were noticed, Fig. 3.11 as the classes population statistics were quite balanced. As confirmation, IMF 3x3 and IRCG 3x3 were then applied to the filtered image (Fig. 3.11) and as expected stability was reached as illustrated in Figures 3.12 and 3.13.

Another test conducted on subimage2 was the application of IMF and IRCG with a 5x5 filter. The use of a larger neighbourhood instead of increasing the quality of the information, enhanced the noise, Fig. 3.14 and Fig. 3.15. The imposition of the filter shape in the production of homogeneous pixel distributions are also clear as noticed for subimage1. A further application of IMF 3x3 did not produce relevant modifications, Fig. 3.16.

IRCG and IMF attempt to combine two types of information at two different levels of abstraction. In other words, each pixel examined, depending on its local information, may determine the modification of global geometric aspects such as original borders displacement or theme re-distribution. Consequences of this are:
1. IRCG emphasises spatial errors introduced by IMF;
2. IRCG does not work when stability of population statistics occur in the filtered image; and
3. IMF and IRCG do not preserve the original proportions of population statistics.

As a minimum, a track of the “evolution” of each local neighbourhood through the iterations should be kept.
Fig. 3.9. Subimage2. A 256x256 section of the entire classified image of Lisbon Bay shown in Fig. 3.3. This image section has been used for experiments on per-pixel filtering.
Fig. 3.10. Filtered image obtained by the application of IMF 3x3 on Subimage2.
Fig. 3.11. Filtered image obtained by the application of IRCG 3x3 on the product shown in Fig. 3.10.
Fig. 3.12. Filtered image obtained by the application of IMF 3x3 on the product shown in Fig. 3.11.
Fig. 3.13. Filtered image obtained by the application of IRCG 3x3 on the product shown in Fig. 3.12.
Fig. 3.14. Filtered image obtained by the application of IMF 5x5 on Subimage2.
Fig. 3.15. Filtered image obtained by the application of IRCG 5x5 to the product shown in Fig. 3.14.
Fig. 3.16. Filtered image obtained by the application of IMF 3x3 to the product shown in Fig. 3.15.
3.4 From Per-pixel Filtering towards an Automatic Per-region Smoothing

The study conducted for this thesis on the state of the art of traditional per-pixel filtering and the experiments conducted on Iterative Majority Filtering based on moving windows applied to classified images has concluded that a contradiction in the processing strategy of per-pixel filtering is the fundamental obstacle to their use in cartographic applications. In fact traditional pixel-based filtering constrains the modification of information at global level (the image) to local details (each pixel neighbourhood) which are geographically, spatially and contextually unconstrained. This strategy is not consistent with the fuller spatial context and combined with its unsupervised iterative performance often results in an uncontrolled loss of important spatial detail in the image affecting the quality of the final information.

More specific considerations may be made on filter size and iterations:

- The level of smoothing depends on the original spatial detail in the image;
- The choice of filter size depends on the original spatial detail in the image;
- The filter size resulting in the least spatial disturbance of the original image is the 3x3 filter;
- The use of filter sizes larger than 3x3 often produces greater confusion in the final product rather than clarifying it. The use of large filter sizes often forces multi pixel objects to assume unnatural shape (generally the filter shape) emphasising already existing errors and/or introducing new erroneous spatial information;
- The choice of the filter size and the number of iterations cannot be decided automatically, depending rather on the uncomputational subjective human expert judgement; and
- Normally the human expert decides (subjectively) the number of iterations to perform or when to stop the filtering activity. Despite this human interaction with the process, the iterative performance of the filtering is uncontrolled.
From the experiments performed on the combination of complementary smoothing algorithms, such as Iterative Majority Filtering and Iterative Reduced Class Growing it is concluded that: although theoretically acceptable, the effective combination of these algorithms does not always clarify the image information, often introducing or emphasising spatial errors in themes. Despite the powerful smoothing performance demonstrated by particular iterative per-pixel filtering algorithms, the products obtained are far from being acceptable for GIS input which requires geographical reference to well defined and independent (although spatially adjacent) geographical entities.

It may be concluded that:

- The lack of a computational model capable of defining objective input and expected (spatial and contextual) conditions for a generally applicable iterative filtering limits the process to an uncontrolled execution;
- Traditional per-pixel filtering is thus not suitable for automatic processing, which requires the definition of an objective model of application which is repeatable and generally applicable; and
- The application of iterative per-pixel filtering to raster classified images based on moving windows is not suitable for automatic post-classification in cartographic generalization activities.

### 3.5 The Automatic Per-region Post-classification Process

An image-consistent automatic post-classification process capable of elaborating a satellite-derived classified image for cartographic generalization purposes may be implemented with the following three essential characteristics:

- **Per-region strategy.** Natural regions automatically extracted from the input image are considered as single and independent spatial entities, characterised by intrinsic attributes and by geometric references to each other (a spatial adjacency relationship);

- **Per-region single step filtering application.** No moving windows or iterations are involved in the post-classification activity. Each spatial entity in the image is analysed and smoothed on the basis of the frequency of contained themes; and
• **Per-region consistent filtering application.** Deletion and enhancement of information within each entity must be spatially consistent and quantitatively proportional to the particular entity.

### 3.6 Automatic Derivation of Spatial Information from Satellite Images

The research conducted for this thesis was aimed at defining a *fully automatic processing chain*, for digital generalization which exploits land cover information derived from satellite-borne sensors. As reported in chapter 2, classified images derived from satellite data must be further processed before being presented in a suitable format for GIS input, rule-based systems adapt themselves well to the land cover mapping problem and are also suitable for the generalization problem.

Post-classification manipulation organised as a step-wise process has an essential role in the realisation of an automatic generalization process. The automatic processing chain developed for this thesis combines traditional image processing and applies new, original rule-based processes and expert systems to derive spatial information suitable for GIS input.

The processing chain is organised as represented in Fig. 3.17. Products derived by traditional image processing (segmentation and classification) are elaborated by the automatic digital generalization process in a step-wise fashion by three original processes which are described in detail in chapters 5, 6 and 7 of this dissertation. The segmentation algorithm is described in chapter 4 as input requirement for the generalization process. The classified image used to test the generalization process was generated by the Neural Network Classifier described in section 2.5.2. The Landsat TM image of Lisbon Bay (Portugal) shown in Fig. 3.2, is the original input for both the classification and segmentation process.

The image subimage2 (Fig. 3.9) used for the experiments on per-pixel filtering described in the previous sections has been used to test the generalization process during the development. This image section has been chosen, rather than subimage1 (Fig. 3.4) because it has larger regions: which allow one to more easily quantify any geometric modification made by the generalization process. Further, the smoothing applied within large regions may also be better evaluated qualitatively and quantitatively.

In this research one single-date classified image has been used to provide information to the generalization processing chain, because the access to one single image was foreseen for
this project. It was also not possible to access to imagery of other areas because it was not part of this specific project.

In brief, the digital generalization process described in this thesis is organised in three main activities concerning the cartographic and statistical generalization of the input land cover data:

- **Integration** of available input data into *per-region data sets* involving the automatic identification of:
  - image-objects;
  - intrinsic attributes for each image-object; and
  - adjacency relationship among image-objects;

- **Geometric generalization** (post-classification) of integrated input data including spatial and thematic simplifications; and

- **Semantic generalization** (*per-region* contextual conversion) of the input classification scheme into the target GIS compatible nomenclature.

The process is automatic, autonomous and dynamic in extracting the necessary knowledge directly from the input data, and is independent form the shape of image-objects. An *image-object* is a spatial entity in the classified image characterised by a closed boundary which uniquely delimits an area on the image. The process satisfies the basic cartographic requirements in producing a final product, which is spatially consistent to the input information, which contains spatial entities geographically connected to ground reference, and which is suitable for direct comparison with CORINE digital land cover/land use maps.
Exploring Current Generalization Methods and an Alternative

Fig. 3.17. Processing Chain for Automatic Derivation of Land Use Information from Satellite Borne Sensors for Direct GIS Input.
4.1 Data Structures and Organisation Supporting Automatic Per-polygon Processing

4.2 Region Adjacency Analysis

4.3 Initial Partitioning of Satellite Image into Atomic Regions

4.4 Data Structures Supporting the Generalization Activity

4.4.1 The Data Structure Poly_Info

4.4.2 The Data Structure Adj_Mat
CHAPTER 4
TOWARDS AUTOMATED GENERALIZATION

4.1 Data Structures and Organisation Supporting Automatic Per-polygon Processing

In this chapter the organisation of the generalization process, the required inputs and data structures fundamental for the generalization activity are presented as an introduction to the following chapters 5, 6 and 7 where a detailed description of activities and techniques supporting the generalization is given.

The generalization process works on independent image-objects (atomic regions and higher level polygons). The algorithms created to process each image-object are shape-independent, and thus generally applicable. The shape-independent treatment of image-objects requires a huge amount of complex controls and verifications (automatically performed by the algorithms) to supplement the lack of information on geometric characteristics. Further, the generalization process combines object attributes with local external context information (attributes of surrounding objects) which are dynamically accessed during the processing when needed. The most important relationship among image-objects for the automatic performance of the generalization process is adjacency. Adjacency among objects and object attributes are automatically derived from the available information during the processing. Objective constraints used for the rules application are automatically calculated from the available data.

4.2 Region Adjacency Analysis

Nichol (a) 1987, (b) 1990) presented a computing strategy for region adjacency analysis of complicated images. This strategy is based on the production of a Region Adjacency Graph (RAG) while the image is analysed. The RAG is particularly suitable for the computation of low level data, which may be a region merging activity on satellite-derived images before their processing for GIS dedicated applications (Barnsley et al., 1993; Barr and Barnsley, 1995). Figure 4.1 illustrates an example of simple segmented image (Z) and the corresponding RAG.
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Fig. 4.1. Example of RAG adapted from [Nichol, 1990]. The image Z is divided in three main regions labelled as a, b, and e. Region b contains region c. Region c contains region d. The relationship of adjacency among regions in image Z is represented in the correspondent RAG which connects any pair of adjacent regions (in this case labelled by a letter form a to e) by an arch (a continuous line from two labels). In the example the RAG shows the subdivision of image Z into regions a, b and e, which are respectively: a is neighbour of b, e is neighbour of b and b is neighbour of both a and e. In the graph is also shown that a and e are not neighbours, that b is also neighbour of c, and that d is the only neighbour of c.

The processing stages which are involved during the production of a RAG are:
1. Initial pre-processing of data for noise reduction and/or preliminary assignment of class labels to regions. This stage is optional and depends on the later use of the RAG;
2. Identification and definitive labelling of all primitive connected regions; and
3. Analysis of the labelled image to retrieve the relationship of adjacency among regions, and storage of information in a linked list which is used to generate the RAG.

The RAG may then be used for spatial and contextual operations which may be the merging of neighbour regions labelled with the same class label; the modified linked list is then used to generate the new “merged” image.

The RAG of an image may be used for both entry and storage of spatial information in a GIS, in which case, during stage 3 of the RAG production, contextual information may also be collected for each region. The RAG may also be used to support complex region-based image processing for which a contextual searching of region information is repeatedly required. The RAG strategy has been selected for such time consuming activities.
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In the generalization process presented in this thesis, the RAG strategy has been used as essential tool for relatively fast and dynamic retrieval of image-object adjacency information, and for the organisation and storage of retrieved information in text files as described in chapter 5. Stage 1 of the RAG production is performed applying a segmentation algorithm to the original satellite image in order to initially divide the image into separate atomic regions. The segmentation algorithm used to derive atomic regions in this thesis is described in the following section. Stage 2 of the RAG production is performed integrating the information derived from the image segmentation with the classified image being generalized. This stage allows the identification of image-objects and the collection (organisation and storage) of contextual information related to each image-object which may be used later during the generalization process. Stage 3 of the RAG production effectively creates the RAG as adjacency matrix, $ADJMAT$ described in section 4.4.2, which allows the identification of neighbours for all image-objects. A complete description of the adjacency between each pair of adjacent objects is also performed at this stage of processing, collecting for example the length (in pixels) and the strength (in gradient magnitude value) of the boundary section shared by two adjacents, as explained in chapter 5. The entire set of information collected and stored while creating the RAG is then used to perform various generalization activities which will finally produce the generalized image.

4.3 Initial Partitioning of Satellite Image into Atomic Regions

To test the generalization process, the Significant Edge Detection (SED) algorithm (Shoenmakers et al., 1992) was used to produce the initial partition of the image section, Fig. 4.2. An extraction from the Landsat TM image of Lisbon Bay, Portugal, (Fig. 3.2) corresponding to subimage2 (Fig. 3.9) was chosen to apply the edge detection algorithm. SED has been chosen, amongst others algorithms (section 2.5.3) for its positive characteristics: SED detects edges using the spectral characteristics of all image channels in order to establish the spectrally “strongest” pixels to form edges. Further, SED connects the edges in closed boundaries (represented in a raster region map) and provides a description in text format, for each region boundary, of the co-ordinates of each boundary-pixels. Closed boundaries represent the spatial limitation of the atomic regions used by the generalization process to generate the spatial basis of the final product, while simplying the low-level classified image.
SED combines filtering, edge detection and region growing techniques (chapter 2) to determine in sequence and consequently:

1. A map of fragmented edges, based on the selection of spectrally “strongest” pixels in the image. For each pixel two vectors, representing respectively the gradient magnitude value of the particular pixel and the direction of the pixel for all the image channels are generated by the algorithm. The selection of the maximum gradient value in the gradient-vector determines the selection of the corresponding direction element in the direction-vector.

2. A map of longer image boundaries, based on a 3x1 filter centred on each pixel in the image and applied to the pixel direction to compute the “likelihood of being an edge”, which produces a map of edge/non-edge pixels. The same filter is then used by an “edge-following” procedure which selects for each edge-pixel in the image the neighbour most likely being an edge and closest to the direction of the central pixel in the filter forming independent boundary-sections.

3. A map of closed boundaries which divides the image into independent parts, based on a 3x3 filter applied to pixels on the boundary-sections to determine the closest independent boundary-section. Closed boundaries are build-up by the connection of two different, close but independent boundary-sections, by adding one connecting pixel.

4. A map of final polygons, based on an iterative region growing procedure, which merges the most similar pixel/regions in the image. The similarity criterion is based on the Euclidean spectral distance (ESD) between two neighbouring pixels/regions.
Fig. 4.2. Initial partition into atomic regions of the section of the satellite image corresponding with the land cover image shown in Fig. 3.9.
4.4 Data Structures Supporting the Generalization Activity

To support the automatic performance of the generalization process, two matrices of C language data structures are used by the computing software: *Poly_Info* and *Adj_Mat*. In the C programming language a structure is a collection of variables referenced under one single reference name providing a means of keeping together related information of different types.

The information implicitly contained in the input data and extracted during the generalization activity is so large and complex that it is subdivided into separate text files, each of which is organised in records. Each record collects information concerning one single image-object. To each object an identifier is associated which is reported in the corresponding records of information. A list of pointers to the address of each record in a file is maintained and dynamically updated for direct access to the required information.

The organisation, per-record and per-type, of the information and the use of *Poly_Info* and *Adj_Mat* matrices are suitable for an automatic retrieval, modification, updating and storage of attributes of image-objects dynamically changing during the execution of the various generalization activities. This data structure also speeds up the process which is very time-consuming.

4.4.1 The Data Structure *Poly_Info*

The matrix *Poly_Info* is used to collect different types of information concerning a single image-object at a time. The size of *Poly_Info* corresponds to the size of the image to generalize, and each matrix entry corresponds to one single pixel in the image. Each entry of the matrix has the data structure _poly_info described below (as declared in the software) carrying information on the image pixel the entry represents:

```c
struct _poly_info{
    int in_out;
    int poly_map;
    int filled;
    unsigned char gen_value;
    
};
```
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- The variable $injout$ is used to map the image-object on the matrix. It carries value 0 if the pixel the entry represents does not belong to the image-object, or 1 if the pixel the entry represents belongs to the image-object;

- The variable $poly_map$ is used to map (and maintain) the original boundary of the image-object under analysis. It carries value 0 if the pixel the entry represents belongs to the boundary of the image-object, or 255 if the pixel the entry represents does not belong to the boundary of the image-object;

- The variable $filled$ is used to map the region enclosed by the boundary of the image-object under analysis. It carries the value 0 if the pixel the entry represents does not belong to the region enclosed by the object boundary, 1 if the pixel the entry represents belongs to the object boundary, or 2 if the pixel the entry represents belongs to the region enclosed by the object boundary; and

- The variable $gen_value$ is used to represent the class associated to the pixel the entry represents. It carries a value representing a class if the pixel the entry represents belongs to the region enclosed by the object boundary, or 0 if the pixel the entry represents does not belong to the region enclosed by the object boundary.

4.4.2 The Data Structure Adj_Mat

The information concerning each image-object is organised, accessed, modified and stored following the theory of the Region Adjacency Graph (RAG) (section 4.2). A RAG may be created by the use of several data structures. For the generalization process developed for this thesis, an adjacency matrix ($Adj\_Mat$) has been used.

$Adj\_Mat$ is used to map the boundary of all image-objects simultaneously, in order to determine how many and which adjacents are in the image for each image-object. This information is then organised in an appropriate text file (more detail in chapter 5).

The size of $Adj\_Mat$ corresponds to the size of the image being generalized. Each entry in the matrix collects information on the corresponding pixel in the image. Each entry in the matrix as a structure, _adj, described below:
struct _adj{
    int adj_poly;
    struct _adj *next;
}

Each entry in $Adj\_Mat$ carries two types of information: $adj\_poly$ indicating the number of object-boundaries touching the pixel the entry represents, and $\ast next$ a pointer to a dynamic list. The number of elements of the list corresponds to the number of image-objects (the adjacents) which have that pixel as boundary-pixel. Each element in the list contains the object-identifier of a single adjacent.
CHAPTER 5 PRE-PROCESSING FOR GENERALIZATION

5.1 Introduction to Automatic Data Integration

5.2 Image-Objects Identification

5.3 Extraction of Independent Image-Objects

5.3.1 FindIntExtPoly() Computing Function

5.4 Extraction of Intrinsic Image-Object Attributes

5.5 Collection and Description of Image-Object Adjacency Information

5.5.1 RAGalgorithm() Procedure

5.6 Per-edge boundary Existence Verification, Spatial Correction and Description

5.6.1 Detection of Oriented Edges

5.6.2 Edges Verification and/or Correction

5.6.2.1 Check on Vertical Edges

5.6.2.2 Check on Free Edges

5.6.2.3 Check on Horizontal Edges

5.6.2.4 Check on Diagonal Edges with Length equal-to 2

5.6.2.5 Convergence of Edges

5.6.2.6 Check on Diagonal Edges with Length longer-than 2

5.7 Discussion on the Automatic Data Integration Process

5.7.1 Verification and Errors in the Integration Process

5.8 Conclusion on the Automatic Data Integration Process
CHAPTER 5
PRE-PROCESSING FOR GENERALIZATION

5.1 Introduction to Automatic Data Integration

As introduced in chapter 4, the generalization process works on independent image-objects obtained by the integration of the two input data: i) the pixel-based geometric description of closed boundaries and ii) the raster land cover image. The automatic integration activity extracts the necessary information from the available data and automatically combines them in a new independent type of information concerning image-objects. The diagram of the architecture of the data integration process is illustrated in Fig. 5.1.

![Diagram of the Architecture of the Automatic Data Integration Process](image-url)
The automatic data integration process analyses sequentially one closed boundary at a time, as they are listed in the text file *poly.dat* which collects the per-pixel geometric description of each closed boundary occurring in the boundary map (subprocess no. 1 in the diagram). The process converts then the per-pixel description of the boundary under analysis into per-edge description and stores the derived information in the file *edge_poly.dat* (subprocess no. 2). The process continues the boundary analysis with the selection of the region enclosed by the boundary, identifying thus the identification of the corresponding atomic region (subprocess no. 3). The area corresponding to the atomic region in the classified image is then analysed by the process for the extraction of intrinsic attributes. The recovered information is organised in the text file *polygon_class.dat* (subprocess no. 4). When all the closed boundaries have been analysed and the file *edge_poly.dat* is completed, the process analyses the relationship of adjacency amongst all atomic regions. The information concerning the adjacency of each pair of adjacent regions is then organised and stored in two text file *adjs_file.dat* and *comparison.dat* (subprocess no. 5). This last action finally produces the integrated data (per-object information organised in text files) necessary to the Low Level Generalization.

The automatic data integration process is a very complex one, and it will be described in this chapter. Computing procedures of the main processes are described in the form of pseudo code. Pseudo code is a suitable format for technical descriptions of computing algorithms avoiding the mention of details concerned with the programming language, variables, control parameters and basic functions involved in the development of the original source code. In the pseudo code presented for some of the main activities, variables and function names in *italic* are taken from the original source code.

The functions and procedures developed for the execution of the entire generalization process are complex and involve the implementation of many other algorithms. Some of these algorithms, if relevant for the description of the main activity are also described.

When the pseudo code is not sufficiently clear to describe an activity, it is substituted by graphic representations and/or by the description of the involved functions and procedures.
5.2 Image-Objects Identification

The input per-pixel description of each closed boundary is stored in a text file, *poly.dat*. The file contains a list of records (variable in length depending on the size of the boundary) each one is associated with one single boundary.

Each boundary is identified in the record by an identifier, an integer value in the range \([1, n]\) where \(n\) is the number of closed boundaries occurring in the boundary map, followed by an integer representing the number of pixel co-ordinates listed for the boundary. It is important to note that the number of co-ordinates listed for each boundary does not necessarily represent the exact number of pixels belonging to the boundary. This derives from the segmentation algorithm used prior to this generalization activity, which uses its own key format for the description of specific boundary pixels. Knowing this makes it essential to map the boundary on a raster matrix and directly count the pixels involved.

Each boundary is described in the record as a list of \((x, y)\) image co-ordinates describing each pixel belonging to the closed boundary. Fig. 5.2 shows the raster representation of 10 boundaries extracted from the closed boundary image shown in Fig. 4.2, and Fig. 5.3 shows an extract of the *poly.dat* file corresponding to these 10 boundaries.

This method of identification of the image boundaries is referred to during the generalization process. The generalization process accepts as input a number of image-objects corresponding to the number of closed boundaries input.

The generalization process works on image-objects at various stages of the processing in order to simplify the appearance of the initial classified image. This principally involves a reduction in the number of input image-objects through various stages of simplification. The number associated with each image-object does not correspond to any priority or spatial relationship among image-objects. For example, the objects 1, 2 and 3 are not necessarily spatially close to each other in a raster representation, nor are they more (or less) important than objects 801, 802 and 803.

During the generalization activity, the association *object-identifier* is transparent to the user, and it is automatically maintained by the process. This allows an anonymous image-object analysis which guarantees an objective modification of image objects based solely on intrinsic object characteristics and on objective spatial relationships dynamically extracted during the execution process.
5.2. Extraction of 10 boundaries from the input closed boundary map shown in Fig. 4.2. The boundaries (1 pixels) are reported as an (X,Y) co-ordinate system corresponding to the raster image matrix. Within each closed boundary lies a integer in the range [1, 10] corresponding to the identifier associated with that particular boundary.
Fig. 5.3. Description of 10 closed boundaries graphically represented in Fig. 5.2, created by the SED algorithm and stored in the text file poly.dat. Poly.dat is organised in records formed by two fields of text lines. For each record the first field always contains one single pair of integers \((a, b)\) indicating the number of boundary pixels \((a)\) and the identifier \((b)\) of the particular boundary described in the record. The second field contains a variable number of pairs of integers \((x, y)\) representing the raster co-ordinates of each pixel belonging to the boundary described in the record. Thus, the first record in this example contains:

<table>
<thead>
<tr>
<th>first field:</th>
<th>second field:</th>
</tr>
</thead>
<tbody>
<tr>
<td>20 1</td>
<td>2,1 3,1 1,2 4,2 1,3 3,3 1,4 3,4</td>
</tr>
<tr>
<td></td>
<td>1,5 4,5 2,6 5,6 2,7 6,7 2,8 6,8</td>
</tr>
<tr>
<td></td>
<td>3,9 6,9 4,10 5,10</td>
</tr>
</tbody>
</table>
5.3 Extraction of Independent Image-Objects

A computing procedure has been created to extract the enclosed region associated with each closed boundary. The procedure called *FindIntExtPoly()* works on the raster representation of one boundary at a time mapped onto a matrix of *_poly_info[]* structure (see section 4.3.1). The procedure consists of a region growing strategy for which the boundary mapped onto the matrix is internally “filled” line-by-line.

The boundary under analysis is scanned line-by-line in the matrix, in order to find intersection pixels between the scan line and the mapped boundary. Depending on the number of intersections occurring on the scan line (i.e. the number of times the scan line touches the boundary), the combination of types of occurring intersections and the status of the *_poly_info[]* structures in the matrix, the procedure recognises regions internal to the closed boundary.

Several controls are necessary during the detection of intersections due to the irregular and unpredictable shape of the boundaries (see for example Fig. 5.2).

The controls are performed for each encountered intersection using a 3x3 moving window mask centred on the intersection. The control procedure responsible for the verification task checks the presence and calculates the spatial distribution of:

a) background pixels,

b) enclosed-region pixels, and

c) boundary pixels

in the local neighbourhood of the intersection, “reading” the information collected in the three types of the structure *_poly_info, in_out, filled and poly_map*. The presence and the combination of the three types of pixels determine the type of the intersection, which may be initial, intermediate or final.

Once an initial intersection is found, the *FindIntExtPoly()* procedure looks for the corresponding final intersection on the scan line detecting an internal region segment, formed by continuous background pixels on the scan line delimited by an initial and a final intersection. Once the final intersection is found, the internal region segment is immediately mapped onto the matrix and the *_poly_info[]* structure updated.
During the search of initial and final intersections, the procedure may encounter *intermediate intersections* (continuous segment of boundary pixels on the scan line) which are automatically excluded from the research and verification.

Fig. 5.4 shows a graphic representation of the status of the matrix of *poly_info()* structures at three different stages of region extraction performed by the *FindIntExtPoly()* procedure.

```
<table>
<thead>
<tr>
<th></th>
<th>_poly_info.in_out</th>
<th>_poly_info.poly_map</th>
<th>_poly_info.filled</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>1 1 1 1</td>
<td>* * * *</td>
<td>1 1 1 1</td>
</tr>
<tr>
<td></td>
<td>1 1 1 1</td>
<td>* * * *</td>
<td>1 1 1 1</td>
</tr>
<tr>
<td></td>
<td>1 1 1 1</td>
<td>* * * *</td>
<td>1 1 1 1</td>
</tr>
<tr>
<td></td>
<td>1 1 1 1</td>
<td>* * * *</td>
<td>1 1 1 1</td>
</tr>
<tr>
<td></td>
<td>1 1 1 1</td>
<td>* * * *</td>
<td>1 1 1 1</td>
</tr>
</tbody>
</table>

a)  

|   | 1 1 1 1           | * * * *             | 1 1 1 1          |
|   | 1 1 1 1           | * * * *             | 1 1 1 1          |
|   | 1 1 1 1           | * * * *             | 1 1 1 1          |
|   | 1 1 1 1           | * * * *             | 1 1 1 1          |
|   | 1 1 1 1           | * * * *             | 1 1 1 1          |

b)  

c)  
```

Fig. 5.4. Image-object identification: the *FindIntExtPoly()* procedure identifies the region enclosed by each closed boundary, via a region growing strategy. The example graphically represents a) the initial, b) an intermediate and c) the final status of the matrix during the performance of the procedure. In these figures the character * substitutes the pixel value 255.
The 3x3 window mask is initially centred at the first entry of the matrix and moved pixel by pixel and line by line until an intersection is found analysing the _poly_info[] variable .in_out. Each of the 8 positions within the mask can be set to a value in the range [0, 1]. Several combinations of the position status are possible, each of which represents a type of intersection. Some intersection types are represented by the same combination of position status therefore the use of the other variables .poly_map and .filled is essential for the final definition of the type of intersection.

Templates, each of which represents one combination of the position status within the mask, have been designed a priori and are used by the control process to verify the intersection. An example of template and processing is given in Fig. 5.5. The complete list of the templates is given in Appendix A.

This template corresponds to two types of intersection, one representing the initial point of an internal-region segment and the other one representing the final point of an internal-region segment.

This template occurs in the closed boundary depicted in Fig. 5.2.

Given the central pixel position (x, y) being the position of the intersection in the 3x3 window mask:

IF

the pixel at the position (x-1,y-1) is set to 0 in the variable .in_out,
the pixel at the position (x,y-1) is set to 1 in the variable .in_out,
the pixel at the position (x+1,y-1) is set to 1 in the variable .in_out,
the pixel at the position (x-1,y+1) is set to 1 in the variable .in_out,
the pixel at the position (x+1,y+1) is set to 2 in the variable .filled

THEN

the intersection is an initial_internal-region_segment type

IF

the pixel at the position (x-1,y-1) is set to 1 in the variable .in_out,
the pixel at the position (x,y-1) is set to 1 in the variable .in_out,
the pixel at the position (x+1,y-1) is set to 0 in the variable .in_out,
the pixel at the position (x-1,y+1) is set to 1 in the variable .in_out,
the pixel at the position (x+1,y+1) is set to 2 in the variable .filled

THEN

the intersection is a final_internal-region_segment type

Fig. 5.5. Example of processing performed by the FindIntExtPoly() procedure while deciding the type of encountered intersection.
5.3.1 FindIntExtPoly() Computing Function

Semantic

The process executed by the main function FindIntExtPoly() performs a region growing activity within the area enclosed by the closed boundary currently mapped on the matrix of _poly_info{} structures. The closed boundary is examined line-by-line in order to identify segments of the region enclosed by the boundary. The process detects on the matrix one internal region segment at a time and fills the boundary region adequately setting the variables .in_out and .filled for each _poly_info{} structure corresponding to the segment. The detection of region segments on a scan line in the matrix influences the detection of region segments lying on the lines below.

Pseudo Code

FOR(each line in the matrix){
  intersection = find_intersection(line);
  check_conditions(intersection);
  type = check_intersection_type(intersection);
  update_intersection_type(type, intersection);
  IF(intersection is not intermediate_intersection){
    IF(initial_intersection is not found yet AND intersection is an
    initial_segment type) THEN
      initial_intersection = intersection;
    ELSE
      IF(final_intersection is not found yet AND initial_intersection is
      found AND intersection is a final_segment type) THEN
        final_intersection = intersection;
      filling_segment(initial_intersection, final_intersection)
    }
    ready_for_next_intersection(intersection);
  }
}
The semantic of each of the functions involved and procedures is given below. In Appendix A lists of conditions and intersection types on which the process execution is based are provided.

\texttt{find\_intersection(line)}

the function scans, pixel-by-pixel, the current line of the matrix and stops when a boundary-pixel is encountered, which becomes the current intersection to examine. The function returns the co-ordinate \( x \) of the current intersection

\texttt{check\_conditions(intersection)}

the procedure extracts the 3x3 neighbourhood of the current intersection in the matrix and fixes the conditions verified over the variables \( .in\_out \) of the structure \_poly\_info{}

\texttt{check\_intersection\_type(intersection)}

the function evaluates the combination of conditions and in case of doubt evaluates the value of the variables \( .filled \) and \( .poly\_map \) of the structure \_poly\_info{} in the same neighbourhood. The function returns the type of intersection, i.e. an integer value in the range [1-66] (Appendix A). The intersection type may be initial\_segment or final\_segment

\texttt{update\_intersection\_type(type, intersection)}

the function sets the control parameters necessary for the final association of the intersection to the initial\_intersection, an intermediate\_intersection or the final\_intersection of the current internal region segment. The setting of the control parameters is based on the type of intersection and the status of the current line (i.e. if any intersection has seen or not)

\texttt{filling\_segment(initial\_intersection, final\_intersection)}

the procedure updates the values of the entries of the matrix assigning the value 1 and the value 2 respectively to the \( .in\_out \) and \( .filled \) variables for each pixel belonging to the selected internal region segment;
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`ready_for_next_intersection(intersection)`

resets the control parameters ready for the search of the next intersection.

### 5.4 Extraction of Intrinsic Image-Object Attributes

**Intrinsic attributes** are those characteristics relating to each object independently of the other objects in the image, such as:

- The *perimeter* (the number of pixels belonging to the object boundary);
- The *area* (the number of pixels belonging to the region enclosed by the object boundary);
- The *land cover population* (the list of the image classes occurring in the region of the classified image corresponding to the internal region of the object); and
- The *population statistic* (the occurrence, i.e. the number of pixels, of each image class occurring in the object region).

These attributes are extracted and associated with each corresponding image-object (referring to the object identifier) once the region enclosed by the object boundary is identified, while still mapped on the matrix of `_poly_info[]` structures.

Perimeter, area and population statistics are types of information which may be easily represented by one single integer value, thus, they are stored in variables globally accessible during the generalization execution. The land cover population, on the contrary, being a list of values, is recorded in a text file, `polygon_class.dat`, associated (referring to the object identifier) to the corresponding image-object. In Fig. 5.6 an extract of the file is shown.

```
... POLY 15 Classes 9,
POLY 16 Classes 1, 2, 3, 4, 5, 6, 8,
POLY 17 Classes 7, 9, 10,
... POLY 21 Classes 5, 7, 8, 9,
... 
```

Fig. 5.6. Text file `polygon_class.dat`. The file is organised in records, each of which collects information concerning with one single image-object. Each record is divided in two numerical fields (in the example from left to right) which are the *object-identifier* and the list of *image-classes* occurring in the region enclosed by the object boundary.
5.5 Collection and Description of Image-Object Adjacency Information

Information concerning the spatial relationship of adjacency between the object and externally touching or internally enclosed objects is extracted from the available data for each image-object in the image. The adjacency matrix $ADJ\_MAT$ (section 4.4.2) is used to collect this information following the strategy of the Region Adjacency Graph presented by Nichol (1990) (section 4.2). The raster representation of two adjacent image-objects is graphically represented in Fig. 5.7 and Fig. 5.8 as detected in the adjacency matrix. Lists of adjacents for each image-object are thus derived from the analysis of $ADJ\_MAT$ as described in section 4.4.2, and stored in a text file, $adjs\_file.dat$, for later access. An extract of the file is shown in Fig. 5.9.

From the information stored in $adjs\_file.dat$ the adjacency between each pair of adjacent objects is calculated and fully described in the text file $comparison.dat$, as shown in Fig. 5.10. *Adjacency attributes* are also collected as:

1. Length in number of pixels of the shared boundary section; and
2. Strength value of the shared boundary section, representing one of the evidences used by the generalization process to merge or to maintain separate two adjacent regions.

The process responsible for the collection and the description of the adjacency among objects is executed by the main procedure $RAGalgorithm()$, and is described in the following section.

![Fig. 5.7. The adjacency between two objects is graphically represented by pixels set to the value 3.](image-url)
Fig. 5.8. The adjacency between two clustering objects is graphically represented by pixels set to the value 3.

Fig. 5.9 Text file \textit{adjs\_file.dat}. The file describes the relationship of adjacency among 10 objects the boundaries of which are represented in Fig. 5.2. Adjacency of a single pixel is not considered in the generalization context. The text file is organised in records, one for each image-object, each record is organised in three data fields (from left to right): the object identifier, the number of adjacent objects and the list of numerical identifiers associated with each adjacent.
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Fig. 5.10. Text file *comparison.dat*. The file describes the spatial adjacency among adjacent image-objects. One pair of adjacent object is described at a time. The text file is organised in records of information, one record for each image-object, each record is organised in 5 data fields (from left to right): the object identifier (P), the adjacent identifier (A), the length (L) of the adjacency, i.e. the number of pixels belonging to the boundary section shared by the object and the particular adjacent, the strength (G) of the shared boundary section, i.e. the sum of the gradient value associated with each pixel belonging to the shared boundary section and derived from the segmentation algorithm, and the list of the raster (x, y) co-ordinates of each pixel belonging to the shared boundary section. The example is referred to the 10 objects the boundaries of which is represented in Fig. 5.2.

The calculation of the value to store in the data field G is described in section 5.5.1.
5.5.1 RAGalgorithm() Procedure

RAGalgorithm() procedure, based on the Region Adjacency Graph strategy of Nichol (1990) described in chapter 4, is responsible for the extraction, calculation and description of the information concerning the adjacency among image-objects. Adjacent objects are those objects which share a section of their boundary or objects which are enclosed by an other one, i.e. contained objects. RAGalgorithm() sequentially calls the following subprocesses:

ADJ_MAT_initialisation()

The procedure allocates the necessary dynamic memory for the adjacency matrix and initialises the matrix entries as described in section 4.3.2.

ADJ_MAT_updating()

The procedure reads the boundary description file, poly.dat, and boundary-by-boundary maps them updating the entries of ADJ_MAT. For each boundary pixel the corresponding entry matrix is updated with the identifier of the object the boundary pixel belongs to.

ADJstatitics()

The procedure reads ADJ_MAT and organises statistics concerning the number of pixels belonging to object boundaries, and the number of pixels belonging to the image background.

FindPolygonsADJS()

The procedure examines one boundary at a time and for each boundary pixel reads the corresponding entry in ADJ_MAT to retrieve a list of object identifiers which all contain that pixel in their boundary if such exists. When all the boundary pixels are examined, the total number of external adjacent objects for that boundary and the complete list of adjacent objects identifiers are stored in the text file adjs_file.dat.

A boundary having no external adjacents is referred as a contained object, which is completely enclosed within the internal region of another object. A contained object is identified in adjs_file.dat as:

\[ P = \text{object identifier} \quad \text{ADJS} \rightarrow 0 \]
This procedure maps the boundary section shared by two adjacent image-objects in the matrix of \_poly\_info/\} structure, as represented in Fig. 5.7 and Fig. 5.8, and describes it as a list of pixel co-ordinates in the text file comparison.dat (Fig. 5.10). Pairs of adjacent objects are analysed one at a time from the text file adjs\_file.dat (Fig. 5.9) to isolate the boundary section shared by each pair of adjacents, to calculate the corresponding length and strength for each shared boundary section, and to store this information (per-pixel description and attributes) in the text file comparison.dat.

To obtain the attribute of each shared boundary section, references are made to the SED algorithm (section 4.3). An intermediate output of the SED algorithm is a raster image of grey values representing the gradient magnitude of each pixel in the original image in a range [0, 255]. Pixels with the maximum gradient magnitude have a value of 255 (white pixels). The raster image is used to calculate the average gradient value of the shared boundary section which represents its strength.

The procedure is responsible for the extraction and description of the adjacency of contained objects.

A contained object is mapped (boundary and enclosed region) on the matrix of \_poly\_info/\} structures recalling the procedure FindIntExtPoly() (see section 5.3) and, one at a time, all image-objects are mapped on the matrix in order to find the object which encloses in its internal region the current contained object, as represented in Fig 5.5.2. Once the enclosing object is identified, the adjacency attributes are calculated and the complete adjacency description reported in the file comparison.dat.
5.6 Per-edge boundary Existence Verification, Spatial Correction and Description

A strategy to transform the input per-pixel boundary description into a *per-edge* boundary description has been designed in order to describe each closed boundary as a list of oriented edges.

**Definition**: an oriented edge is a sequence of continuous boundary pixels satisfying a specific spatial constraint on *contiguity of direction*.

Edges may be horizontally, vertically or diagonally oriented as represented in Fig. 5.11. A closed boundary may thus be defined as a set of linked edges, in which each edge is concatenate to two different edges, Fig. 5.12.

![Fig. 5.11. Oriented Edges: 1) Horizontal Edge, 2) Vertical Edge, 3) Right Diagonal Edge and 4) Left Diagonal Edge.](image)

![Fig. 5.12. A closed boundary formed by two horizontal edges, two vertical edges and two diagonal edges.](image)

The advantages for such a boundary description are:

- The possibility of a direct per-edge comparison of boundaries between image-objects and GIS polygons any time during the generalization process;
- The independence of the generalization process from the input data format; and
- The verification of the correctness of input closed boundaries.
A hierarchical control-based strategy for the spatial verification and correction of closed boundaries has thus been designed and the algorithm PolygonEdgeDescription() developed. The execution of this complex algorithm is based on the matrix of _poly_info[] structures, which stores for the analysis task one closed boundary at a time, and the structure _stack_edge[] used to store the list of edges detected for the currently examined closed boundary. The structure _stack_edge[] allows a dynamic modification of edges while processing, and allows a cross analysis of several edges at once and is organised as following:

```
structure _stack_edge{
    int ch;    code for potential, accepted or eliminated edge
    int ty;    edge orientation: 1, 2, 3 or 4
    int sx;    x co-ordinate of the initial extreme of the edge
    int sy;    y co-ordinate of the initial extreme of the edge
    int ex;    x co-ordinate of the final extreme of the edge
    int ey;    y co-ordinate of the final extreme of the edge
    int length; number of contiguous pixels forming the edge
}
```

For each closed boundary the algorithm PolygonEdgeDescription() is activated. There are three main activities of the algorithm:

1. Detection of oriented edges, referred to as potential edges;
2. Spatial verification of correctness of the potential edges; and
3. Edge-by-edge description of the closed boundary stored in the text file edge_poly.dat.

PolygonEdgeDescription() (listed below) consists of two sets of sequential procedures (Find and Check) which are responsible respectively for the detection of potential edges and for their spatial verification. Find and Check procedures are described respectively in section 5.6.1 and 5.6.2. The third activity performed by the Writing_PE_Description() procedure writes the file edge_poly.dat, an extract of which is shown in Fig. 5.13.
PolygonEdgeDescription()
{
    _stack_edge_initialisation();
    FindHorizontalEdges();
    FindVerticalEdges();
    FindRightDiagonalEdges();
    FindLeftDiagonalEdges();
    CheckVerticalEdges();
    CheckFreeEdges();
    CheckHorizontalEdges();
    IF(horizontal edges exist)
      THEN cont_vertex = FindVertex12();
    CheckDiagonal2Edges(cont_vertex);
    CheckDiagonalM2Edges(cont_vertex);
    Writing_PE_Description();
}

# Fig. 5.13. Text file edge_poly.dat is organised in records of
# Polygon 1
# Polygon 1 information; each record corresponds to the geometric description of a
# 1 2 2 1 3 1
# single image-object. Each record is divided in a number of fields each
# 1 2 4 10 5 10
# describing a single edge. The number of fields in the record depends
# 2 4 1 2 1 5
# on the image-object. In this example the image-object no. 1,
# 2 2 3 3 3 4
# graphically represented in Fig. 5.2, is described as a set of 13 oriented
# 2 3 2 6 2 8
# edges. The record of information related to this object is divided in 13
# 2 3 6 7 6 9
# fields.
# Each field contains six values which (left to right) represents: the edge
# 3 2 3 1 4 2
# orientation, the length in number of pixels, starting x co-ordinate,
# 3 4 3 4 6 7
# starting y co-ordinate, ending x co-ordinate and ending y co-ordinate.
# 3 2 1 5 2 6
# 3 3 2 8 4 10
# 4 2 2 1 1 2
# 4 2 4 2 3 3
# 4 2 6 9 5 10
#
5.6.1 Detection of Oriented Edges

The procedures described in this section are necessary for the detection of oriented edges from the closed boundary map:

FindHorizontalEdges()

This procedure reads the matrix row-by-row from left-to-right looking for a sequence of contiguous pixels lying on the same row. The pixels belonging to a horizontal edge are characterised by ordinary increasing x co-ordinate, and the same y co-ordinates. For example the edge represented by the sequence of pixel co-ordinates:

(1, 3) (2, 3) (3, 3) (4, 3) (5, 3)

is a horizontal edge and it is stored in the list of edges _stack_edge{} as:

\[
\begin{align*}
    ty &= 1; \\
    sx &= 1; \\
    sy &= 3; \\
    ex &= 5; \\
    ey &= 3;
\end{align*}
\]

FindVerticalEdges()

This procedure reads the matrix column-by-column from top-to-bottom looking for a sequence of contiguous pixels lying on the same column. The pixels belonging to a vertical edge are characterised by the same x co-ordinate, and ordinary increasing y co-ordinates. For example the edge represented by the sequence of pixel co-ordinates:

(10, 9) (10, 10) (10, 11) (10, 12) (10, 13)

is a vertical edge and it is stored in the list of edges _stack_edge{} as:

\[
\begin{align*}
    ty &= 2; \\
    sx &= 10; \\
    sy &= 9; \\
    ex &= 10; \\
    ey &= 13;
\end{align*}
\]
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*FindRightDiagonalEdges()*

This procedure reads the matrix row-by-row from top-to-bottom and column-by-column from left-to-right looking for a sequence of contiguous pixels lying on contiguous rows. The pixels belonging to a right diagonal edge are characterised by ordinary increasing \( x \) co-ordinate, and ordinary increasing \( y \) co-ordinates. For example the edge represented by the sequence of pixel co-ordinates:

\[
(10, 9) \ (11, 10) \ \ (12, 11) \ \ (13, 12) \ \ (14, 13)
\]

is a right diagonal edge and it is stored in the list of edges \( \_stack\_edge[] \) as:

\[ty = 3;\]
\[sx = 10;\]
\[sy = 9;\]
\[ex = 14;\]
\[ey = 13;\]

*FindLeftDiagonalEdges()*

This procedure reads the matrix row-by-row from top-to-bottom and column-by-column from right-to-left looking for a sequence of contiguous pixels lying on contiguous rows. The pixels belonging to a left diagonal edge are characterised by ordinary decreasing \( x \) co-ordinate, and ordinary increasing \( y \) co-ordinates. For example the edge represented by the sequence of pixel co-ordinates:

\[
(10, 9) \ (9, 10) \ (8, 11) \ (7, 12) \ (6, 13)
\]

is a left diagonal edge and it is stored in the list of edges \( \_stack\_edge[] \) as:

\[ty = 4;\]
\[sx = 10;\]
\[sy = 9;\]
\[ex = 6;\]
\[ey = 13;\]

---
5.6.2 Edges Verification and/or Correction

The Checks procedures are responsible for the verification of potential edges stored in the structure _stack_edge{} by applying spatial controls to each potential edge. An edge which satisfies a specific spatial constraint may be immediately eliminated, accepted or modified.

The controls, hierarchically organised, are specific for each type of edge, and for each spatial constraint a subsequent action is associated. The length of a potential edge is essential for the application of spatial constraints and the activation of the appropriate subsequent action: edges are analysed as having length 2 (two pixels long) or longer than 2 (longer than two pixels). The potential edges are analysed following an order of priority: vertical edges have the highest priority, followed by the horizontal edges and then the diagonal edges.

One of the main tasks of the conversion of the edge description is to determine a direct correspondence between a raster closed boundary and a GIS polygon in vector format. The reason for these controls is graphically represented in Fig. 5.14. The result of the application of the verification controls is shown in Fig. 5.15, where the corrected closed boundary image corresponding to the boundary image shown in Fig. 4.2 is represented.

Fig. 5.14. Graphic representation of the verification of edges. The potential oriented edges associated with the raster representation of a closed boundary (A) are analysed (B), corrected and/or deleted in order to fix the edges which are spatially meaningful in a correspondent vector format (C).
Fig. 5.15. Corrected closed boundary map.
5.6.2.1 Check on Vertical Edges

Vertical edges have the highest priority of acceptance, therefore they are immediately accepted. However a control (Control 1) is necessary in order to avoid intersections between an extreme of the vertical edge with an intermediate pixel of a horizontal potential edge.

The following definitions are fundamental in this context:

**Definition:** Initial extreme of an edge is the starting pixel of an edge. For example, in a horizontal edge the initial extreme is arbitrarily defined as the pixel having the lowest \( x \) coordinate.

**Definition:** Final extreme of an edge is the final pixel of an edge. For example, in a horizontal edge the final extreme, consistent with the above definition, is the pixel having the highest \( x \) coordinate.

**Definition:** Intermediate pixel is a pixel belonging to an edge which is not the initial extreme nor the final extreme.

Two examples of the situation under analysis are graphically represented in Figures 5.16 and 5.17.

![Figure 5.16](image1.png)

**Fig. 5.16.** Example of control 1 for vertical edges. The beginning situation A shows three potential edges (in total there are 7 potential edges, but just the three highlighted are meaningful for this example): a horizontal, a vertical and a right diagonal edge. The vertical edge is a false edge and deleted to give the final situation B.

![Figure 5.17](image2.png)

**Fig. 5.17.** Example of control 1 for vertical edges. The beginning situation A shows three potential edges (in total there are 9 potential edges, but just the three highlighted are meaningful for this example): one horizontal edge, one vertical edge and one right diagonal edge. The vertical edge is corrected to give the final situation B which is acceptable in vector format.
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Pseudo code associated with Control 1 on the acceptance of Vertical Edges is:

IF an extreme of the vertical edge coincides with an intermediate pixel of a horizontal edge
THEN
  IF the length of the vertical edge is equal to 2
  THEN the vertical edge is removed from the list _stack_edge{}
  ELSE the vertical edge is shortened of one pixel, from the extreme under analysis
ELSE the vertical edge is accepted

5.6.2.2 Check on Free Edges

Any edge of the form represented in Fig. 5.18 is called a free edge in the context of this thesis.

Definition: A free edge is an edge which is connected to only one other edge or is not connected to any other edge at all.

The procedure controls (Control 2) the initial and final extremes of each potential and accepted edge in order to detect extremes which are not connected to any other edge in the list _stack_edge{}.

Pseudo code associated with Control 2 applied to each potential and accepted edge in the list _stack_edge{} is:

IF the initial_extreme of the currently analysed edge is not connected
to any potential or accepted edge
THEN the edge is a free edge and must be eliminated from
the list _stack_edge{}
ELSE
  IF the final_extreme of the currently analysed edge is not connected
to any potential or accepted edge
  THEN the edge is a free edge and must be eliminated from
  the list _stack_edge{}
ELSE the currently analysed edge is not a free edge

IF the currently analysed edge is a potential edge
THEN the currently analysed edge is available for further controls of existence
ELSE do nothing

Fig. 5.18. A free edge erroneously associated with the closed boundary during the initial partitioning of the image is highlighted with a white line.

5.6.2.3 Check on Horizontal Edges

This control (Control 3) verifies that none of the horizontal edges intersects orthogonally any vertical edge. In the case of potential edges verifying this spatial situation, the control procedure eliminates or corrects it. An example of the situation under analysis is graphically represented in Fig. 5.19. Pseudo code associated with Control 3 on the acceptance of Horizontal Edges is:

IF an extreme of the horizontal edge coincides with an intermediate point of a vertical edge
THEN
   IF the length of the horizontal edge is equal to 2
   THEN the horizontal edge is removed from the edges list
   ELSE the horizontal edge is shortened by one pixel from the extreme under analysis, and the new horizontal edge is available for further controls
   ELSE the horizontal edge is available for further controls
5.6.2.4 Check on Diagonal Edges with Length equal-to 2

In order to understand the check procedure below, the following definition is required.

Definition: A vertex is the pixel which joins together an extreme of a vertical edge and an extreme of a horizontal edge, i.e. forming a 90° angle.

Two controls (Controls 4 and 5) are applied to diagonal edges which are two pixels long. Control 4 is performed to eliminate those diagonal edges departing from (or ending on) a vertex. Control 5 is performed to eliminate those diagonal edges intersecting a vertical or a horizontal edge. Two examples of the situation under analysis are graphically represented in Figures 5.20 and 5.21 respectively corresponding to control 4 and control 5.
Pseudo code associated with Control 4 on the acceptance of Diagonal Edges is:

IF an extreme of a diagonal edge of length 2 coincides with a vertex
THEN the diagonal edge is removed from the list \_stack\_edge{}
ELSE do nothing

Pseudo code associated with Control 5 on the acceptance of Diagonal Edges is:

IF an extreme of a diagonal edge of length 2 coincides with an intermediate pixel of a vertical edge or of a horizontal edge
THEN the diagonal edge is removed from the list \_stack\_edge{}
ELSE do nothing

5.6.2.5 Convergence of Edges

In order to understand the content of this section the following definitions are required.

**Definition:** An *Intersection* is a boundary pixel common to two or more edges. A vertex is a particular intersection between a horizontal edge and a vertical edge. Intersections of intermediate pixels are not considered.

**Definition:** *Convergence* is the number of edges converging on the same intersection.
The convergence value associated with an intersection is initially set to the value 0, and is calculated as described below in terms of Pseudo code:

\[
\text{FOR (each accepted edge in the list } \_\text{stack_edge}()) \{ \\
\text{IF an extreme of an accepted edge coincides with the intersection} \\
\text{THEN increase the convergence_value by 1} \\
\text{ELSE do nothing} \\
\}
\]

The convergence is then verified on all edges in the list:

\[
\text{IF convergence_value = 0} \\
\text{THEN} \\
\text{FOR (each edge, accepted and non- accepted, in the list } \_\text{stack_edge}()) \{ \\
\text{IF an intermediate pixel of an edge coincides with the intersection} \\
\text{THEN set the convergence_value to -1} \\
\text{ELSE do nothing} \\
\}
\]

ELSE do nothing
The convergence on non-accepted diagonal edge longer than two pixels is also verified:

\[
\text{IF } \text{convergence\_value} = 0 \\
\text{THEN} \\
\text{FOR each non-accepted diagonal edge longer than two} \\
\text{pixels} \\
\text{IF an extreme of an edge coincides with the} \\
\text{intersection} \\
\text{THEN increase the convergence\_value by 1} \\
\text{ELSE do nothing} \\
\} \\
\text{ELSE do nothing}
\]

5.6.2.6 Check on Diagonal Edges with Length longer-than 2

Three hierarchical controls (Controls 6, 7 and 8) are involved in the verification of diagonal edges longer than two pixels. An example representing a closed boundary of three diagonal edges longer than two pixels is given in Fig. 5.22.

Fig. 5.22. Example of control for diagonal edges longer than two pixels. The initial situation A shows a raster closed boundary with 8 accepted edges (white) and three diagonal edges (red, yellow and green) still to be checked. Controls 6, 7 and 8 perform the correction on the three diagonal edges, giving the final set of accepted edges (situation B).
Control 6 is applied to each diagonal edge longer than two pixels in order to verify the condition for which a diagonal edge is acceptable when its pixels do not coincide with extremes nor intermediate pixels of accepted edges. The red diagonal edge verifies this condition and thus is immediately accepted.

Pseudo code associated with Control 6 on acceptance of Diagonal Edges is:

IF a diagonal edge longer that two pixels does not present pixels which coincides with extremes nor intermediate pixels of accepted edges
THEN
the diagonal edge is accepted in the list \_stack\_edge{}
ELSE do nothing

Control 7 is applied to those diagonal edges not satisfying the previous control. Each of those edges is systematically corrected by dividing it in two or more diagonal segments based on existing intersections. The segments satisfying specific spatial conditions are accepted as independent diagonal edges, while other segments are discarded. If at least one segment is accepted as an existing diagonal edge, the original diagonal edge is eliminated from the list \_stack\_edge{}. The yellow diagonal edge represented in Fig. 5.22 is corrected by Control 7 as graphically described in Fig. 5.23.

Control 7 works on three consequent intersections, called A, B and C, at a time, which generate three segments, AB, BC and AC, on the diagonal edge currently under exam. The control procedure applying convergence constraints to the intersections, chooses the segment which is spatially acceptable and deletes the others from the original diagonal edge. The convergence constraint is calculated for each intersection as described in Table 5.1. Three new intersections are then selected, with the constraint that the new A coincides with the previous C intersection. The control goes on until the end of the original diagonal edge is reached.
Pre-processing for Generalization

A\_conv = 1, B\_conv = 1, C\_conv = 0
A\_conv = 1, B\_conv = 1, C\_conv = -1
A\_conv = 1, B\_conv = 1, C\_conv = 2
A\_conv = 1, B\_conv = 2, C\_conv = 0
A\_conv = 1, B\_conv = 2, C\_conv = -1
A\_conv = -1, B\_conv = 1, C\_conv = 2

\textit{corresponds to the extraction of section AB}

A\_conv = 2, B\_conv = 1, C\_conv = 1
A\_conv = -1, B\_conv = 1, C\_conv = 1

\textit{corresponds to the extraction of section BC}

A\_conv = 1, B\_conv = 2, C\_conv = 1

\textit{corresponds to the extraction of section AC}

Other combinations of convergence values result in abandoning of the currently analysed segment and the extraction of new A, B and C intersections and the identification of a new diagonal segment to analyse.

Table 5.1. Table of combination of convergence values used by control 7 to correct potential diagonal edges longer than two pixels.

Fig. 5.23. Graphic representation of the correction of diagonal edge coloured in yellow and corresponding to the example described in Fig. 5.22.

The convergence values of A, B and C intersections are:

\begin{itemize}
  \item convergence in A is A\_conv = -1
  \item convergence in B is B\_conv = 1
  \item convergence in C is C\_conv = 1
\end{itemize}

The combination of convergence values corresponds to the elimination of the section AB and the acceptance of the section BC as a new diagonal edge.
Pseudo code associated with Control 7 on acceptance of Diagonal Edges is:

\[
\begin{align*}
\text{FOR (each diagonal segment delimited by intersections A, B, C)} & \{ \\
\text{IF A\_conv, B\_conv and C\_conv respect the table of the accepted convergence} & \text{THEN} \\
\text{- the appropriate section of the segment under analysis is extracted} & \\
\text{- (x,y) co-ordinates of the section extremes and the length of the section is calculated} & \\
\text{- the section and its attributes are introduced into the list _stack_edge/} & \text{as an accepted diagonal edge} \\
\text{ELSE do nothing} & \\
\} \\
\text{IF at least one section has been accepted as a new diagonal edge} & \text{THEN the original diagonal edge is eliminated from the list _stack_edge/} \\
\text{ELSE do nothing} & \\
\end{align*}
\]

Control 8 is activated for those diagonal edges neither accepted nor corrected by the previous controls. This last control corrects an edge by extracting one diagonal section at a time from the original edge working solely on two intersections, A and B. For each intersection, the control process checks the existence of vertexes and/or intermediate pixels of already accepted edges at the right, the left, above or below the two intersections. Depending on vertexes and/or the intermediate pixels of other edges involved in the two intersections, the segment AB may be accepted as an independent diagonal edge or discarded. In any case a new AB segment is extracted with the spatial constraint that the A intersection of the new segment corresponds to the B intersection of the previous segment. This continues until the end of the original diagonal edge is reached. In the case that at least one segment is accepted as the diagonal edge, the original edge is eliminated from the list _stack_edge/. The situation described above is verified by the green diagonal edge, shown in Fig. 5.22 and its correction is graphically represented in Fig. 5.24.
Fig. 5.24. Example of correction performed by control 8 on a diagonal edge longer than two pixels.

(1) Initial situation. The diagonal edge coloured in green is checked. Intersection A is directly connected with vertex v₁ through the vertical edge associated with the vertex. Intersection B is directly connected with vertex v₁ through the horizontal edge associated with the vertex. The convergence values for intersections A and B are:

- Convergence value in A is $A_{\text{conv}} = 1$ calculated excluding the segment AB and the vertical edge associated with vertex v₁
- Convergence value in B is $B_{\text{conv}} = 0$ calculated excluding the segment AB and the horizontal edge associated with the vertex v₁
- Convergence value in v₁ is $\text{conv} = 1$

Following the table of convergence value shown at page 115, the segment AB has no spatial proof of existing, and a subsequent diagonal segment is chosen for verification, as represented in (2).

(2) Intersection A is directly connected with the vertex v₁ through the horizontal edge forming that vertex. Intersection B is directly connected with vertex v₂ through the vertical edge forming that vertex. Vertexes v₁ and v₂ are not coincident thus the segment AB is accepted as diagonal edge with no further controls on convergence values. The consequent diagonal segment is then extracted, as graphically represented in (3).

(3) Intersection A is directly connected with vertex v₂ through the vertical edge. Intersection B is directly connected with vertex v₂ through the horizontal edge. The convergence values for intersections A and B are:

- Convergence value in A is $A_{\text{conv}} = 0$ calculated excluding the segment AB and the vertical edge associated with the vertex v₂
- Convergence value in B is $B_{\text{conv}} = 1$ calculated excluding the segment AB and the horizontal edge associated with the vertex v₂
- Convergence value in v₂ is $\text{conv} = 1$

Following the table of convergence value shown at page 115, the segment AB has no spatial proof of existing, and a consequent diagonal segment is extracted, as represented in (4).

(4) Final situation. The original diagonal edge is eliminated from the list _stack_edge_ and the new diagonal edge two pixels long coloured in green is added to the list _stack_edge_ as accepted edge.
Pre-processing for Generalization

Pseudo code associated with Control 8 on acceptance of Diagonal Edges is:

UNTIL (the final extreme of the original diagonal edge is not reached) {
- Isolate intersections A and B
- Find, if existing, a vertex va directly connected (horizontally or vertically) to A
- Find, if existing, a vertex vb directly connected (horizontally or vertically) to B
IF va coincides with vb
THEN
  - Calculate A_conv
  - Calculate B_conv
  - Calculate conv_va
  IF A_conv = 0 AND conv_va = 2
  THEN
    - the edge connected to B through the vertex vb (va) is eliminated
    - search for another B intersection
  ELSE
    IF A_conv = 1 AND conv_va = 2 AND B_conv = 1
    THEN
      - the edge connected to A through the vertex va (vb) is eliminated
      - search for another B intersection
    ELSE (the other combinations)
      - the segment AB is no longer considered because it is not spatially significant
      - skip to another AB segment
  ELSE IF va does not coincide with vb
  THEN
    - the segment AB is spatially significant and accepted as a new diagonal edge
    - calculate the attributes (x,y co-ordinates and length) for the new diagonal edge
    - select another AB segment
  ELSE
    IF the x co-ordinate of va = 0 AND y co-ordinate of va = 0 AND
      the x co-ordinate of vb not = 0 AND y co-ordinate of vb not = 0 AND
conv_vb = 2

THEN
- the segment AB is spatially significant and accepted as a new diagonal edge
- calculate the attributes (x,y co-ordinates and length) for the new diagonal edge
- select another AB segment

ELSE IF the x co-ordinate of va not = 0 AND y co-ordinate of va not = 0
AND the x co-ordinate of vb = 0 AND y co-ordinate of vb = 0 AND conv_va = 2
THEN
- the segment AB is spatially significant and accepted as a new diagonal edge
- calculate the attributes (x,y co-ordinates and length) for the new diagonal edge
- select another AB segment

ELSE IF the x co-ordinate of va = 0 AND y co-ordinate of va = 0
AND the x co-ordinate of vb not = 0 AND y co-ordinate of vb not = 0
THEN
- the segment AB is spatially significant and accepted as a new diagonal edge
- calculate the attributes (x,y co-ordinates and length) for the new diagonal edge
- select another AB segment

ELSE
- the edge connected to B through the vertex vb (va) is eliminated
- search for another B intersection

} IF at least one segment has been accepted as a new diagonal edge
THEN the original diagonal edge is eliminated from the list _stack_edge{}
ELSE do nothing
5.7 Discussion on the Automatic Data Integration Process

The minimum essential input required for the objective and automatic performance of the generalization process is:

1. Raster image classification representing the input land cover information;
2. Raster region edge map derived, via image segmentation, from the original satellite image used to produce the input classified image;
3. Geometric description (in text format) of each input region closed boundary; and
4. Access to per-pixel gradient information used and derived by the segmentation algorithm while forming region closed boundaries.

The spatial description of each closed boundary is essential for the entire generalization process: from the closed boundary description the associated internal region and object attributes may be automatically derived. The initial process of the generalization activity, concerning the automatic integration of input data uses the boundary description of each input image-object to retrieve, calculate, and organise the information necessary for the generalization activity.

RAGalgorithm(), FindIntExtPoly() and PolygonEdgeDescription() will be systematically re-activated at different stages of the processing chain to support the generalization activities which perform object modifications.

The use of raster matrices on which to map the raster representation of each boundary is a suitable strategy to support automatic and dynamic processing, avoiding user interaction. It allows the independent treatment of each image-object while maintaining the absolute geographic reference with the other image-objects.

The use of the Region Adjacency Graph (RAG) for the retrieval, organisation and description of the spatial relationship of adjacency among image-objects is an appropriate solution to support automatic processing in dynamic access and updating of information with a vast number of image-objects. RAGalgorithm() is responsible for the extraction of information concerning with each image-object, as intrinsic attributes or as the spatial relationship of adjacency, and the organisation of this information into per-type and per-object specific text files. The combination of the RAG strategy with the use of text files organised in records of information, allows direct access to the required information avoiding redundant
processing. The processing time of \textit{RAGalgorithm()} is directly related to the complexity of the boundary map: the larger the number of image-objects the longer the time required to retrieve the adjacency information. To reduce this processing time, parallel processing is a suitable solution one process per object.

5.7.1 Verification and Errors in the Integration Process

\textit{FindIntExtPoly()} and \textit{PolygonEdgeDescription()} are working processes still at a prototype stage. For their development samples of adjacent closed boundaries have been randomly selected from the entire set of input closed boundaries, which contains 2032 closed boundaries. The performance verification of each process involves the execution of the entire process for one single boundary at a time. When a sample of boundaries was correctly processed by the two algorithms another sample was selected for further verification of the algorithm.

Both processes may be affected by input errors and during the generalization process by error propagation. To quantify the success of their performance a 100\% correct closed boundary map should be used, such as a digitised closed boundary map stored in a GIS and provided by raster description. The generalization process in fact works with data derived from any source (satellite imagery, digital maps and others) presented in raster format.

Without a specific description of error types (if existing) in the input segmented data, it is very difficult to determine the existence or not of spatial errors in the boundary description. Two types of errors, which may affect the performance of \textit{FindIntExtPoly()} and \textit{PolygonEdgeDescription()}, are: free edges and gaps in the input boundary map.

Free edges and small gaps (one or two missing pixels) in the sample boundaries along the image borders have been discovered. Discovering gaps on boundaries which do not lie on the image border is more difficult: in fact a gap on one boundary may be “hidden” by the adjacency with surrounding boundaries correctly described.

The overall performance of \textit{PolygonEdgeDescription()} on the entire set of closed boundaries, was made comparing the input boundary map with the output map. The two maps, shown in Fig. 4.2 and Fig. 5.15, are identical with the exception of free edges occurring in the input map, which have been eliminated by the process.
FindIntExtPoly() and PolygonEdgeDescription() are still prototypes and may not recognise all hidden gaps. The existence of unknown hidden gaps, may cause the propagation of these spatial errors and so some new one may be expected to be generated in processing.

The performance of FindIntExtPoly() and PolygonEdgeDescription() will be further analysed and discussed in chapter 6 in relation to the Low Level Generalization, which performs spatial and thematic modifications on the input image-objects requiring a complete up-to-date description of new objects.

5.8 Conclusion on the Automatic Data Integration Process

The data integration process presented in this thesis is capable of automatically extracting and combining the essential detail from two independent data sets. For a generally applicable process capable of effective data integration and production of GIS compatible data the definition of a model of spatial entity or image-object is necessary. An image-object consists of:

- A closed boundary and associated geometrical description;
- An area enclosed by the closed boundary;
- A set of intrinsic attributes; and
- The description of the spatial relationship of adjacency with other entities.

The Automatic Data Integration Process developed for the generalization activity dynamically satisfies all of the following requirements:

1. Extracts the area enclosed by each closed boundary;
2. Extracts and organises the information concerning the intrinsic attributes of each image-object;
3. Extracts, organises and describes the information concerning the spatial relationship of adjacency among image-objects; and
4. Organises the per-object integrated information in records of text files.

The process responsible for the automatic extraction of the area enclosed by each closed boundary (1) has been demonstrated to be:

- Effective in processing a large volume of data;
- Effective in selecting only the essential information to be permanently stored during the entire working session;
• Effective in combining templates and raster matrices during execution; and
• Appropriate strategy for automatic processing in combining templates and raster matrices and in allowing the direct extraction of intrinsic attributes for any image-object.

The process responsible for the extraction of information concerning the spatial relationship of adjacency among image-objects (2) is based on the Region Adjacency Graph (RAG) combined with the use of raster matrices showing that:

• The RAG strategy is appropriate for an automatic, autonomous and dynamic process such as the generalization process; and
• The use of the RAG strategy, the organisation of information of image-objects in records of text files, and the support of raster matrices is a successful combination for automatic, autonomous and dynamic processing of a large volume of raster data.

The automatic data integration process also has the ability to convert the input per-pixel geometric description of each closed boundary into a per-edge boundary geometric description (3) by an automatic process based on the per-edge boundary description commonly used in GIS. The process responsible for the conversion from per-pixel to per-edge description of each entity boundary is useful tool:

• In the case of direct per-edge comparison between an image-object and a CORINE polygon (or similar); and
• For the spatial verification of each closed boundary.
CHAPTER 6 GEOMETRIC GENERALIZATION

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CHAPTER 6
GEOMETRIC GENERALIZATION

6.1 Introduction to Geometric Generalization

The integrated image generated by the Automatic Data Integration process (chapter 5) is subjected to Geometric Generalization in order to reduce the image complexity. The geometric simplification of the image is performed by three main activities which work on individual atomic regions. Each activity produces at the end of its operations a raster image and updates the related text information. The three activities are:

1. Per-object Reduction of Gradual Change Zones;
2. Automatic Spatial Generalization of atomic regions; and
3. Per-object Thematic Smoothing.

The integration of the closed boundary image with the classified image, shown in Fig. 6.1, generates zones of mixed pixels identifying areas where the passage from one category to another is gradual. Those zones of mixed pixels clearly identifiable along the boundaries of objects containing one single class, have an inappropriate geometry to be retained in a generalization context. The Automatic Recognition and Contextual Treatment of Gradual Change Zones is the first activity performed by the geometric generalization. This activity detects such zones in the image and changes their thematic attributes to be more compatible with their neighbours. This activity is described in detail in sections 6.2 and 6.3.

The number of closed boundaries contained in a boundary image and the image size may be used to indicate the level of the image complexity. The closed boundary image used to test the generalization process (Fig. 4.2), the size of which is 256x256 (rows and columns), contains 2032 region boundaries, the perimeters of which vary from 3 pixels up to some hundreds of pixels. It may be stated that the image of atomic regions is very complex, and contains many very small image-objects which are inappropriate for individual context simplification (the exception is the object representing the River Tejo which is easily recognisable in Fig. 4.2 and Fig. 3.9 as a long, wide and uniform region delimited by two linear and sub-parallel edges tracing the shape of a water course). The Spatial Generalization activity (described in section 6.4) reduces the number of atomic regions in the objects image via a rule-based merging activity, which merges “small” atomic regions to the most
appropriate adjacent class creating an output image of main regional closed boundaries forming higher level polygons.

The *Thematic Smoothing activity* (described in section 6.5) is then applied to the image of higher level polygons to reduce the number of image classes associated with each higher level polygon. This activity is based upon the principle of the traditional Majority Filtering algorithm in combination with the Reduced Class Growing algorithm, but revised and adapted to *per-object* applications, as explained in chapter 4.
Fig. 6.1. Overlay of the closed boundary map onto the classified image. Differences in the position of regional borders are evident between the two images.
6.2 Comparison of Different Maps of the Same Geographical Area

Overlaying the closed boundary map to the classified image, as shown in Fig. 6.1, shows differences in the position of natural region boundaries. An example is the object corresponding to the River Tejo on the edge of which lie small image-objects. The majority of these image-objects are divided in two principal areas: an area opposite to the river edge which contains mixed categories, and a minor homogeneous area associated to the image-class “water” adjacent and distributed parallel to the river edge. These objects are all considered polygons being zones where the passage from the category “water” and the adjacent land cover categories is gradual. These polygons are “long and narrow” and generally distributed along the boundaries of image-objects containing one single class. These polygons look like sliver polygons, and have an inappropriate geometry to be retained for further processing. These polygons can be considered as similar in character to sliver polygons, and can be treated by techniques described in (Chrisman 1989; Chrisman and Lester, 1991; Lester and Chrisman, 1991).

Map makers and users know well that two different maps representing the same geographical area with the same classification scheme often differ not only when the two maps have been produced by two different cartographers, but also when the maps have been produced by one single expert using different techniques or designed at different times. In this section, differences arising from the comparison of maps representing the same geographical area, but produced with different techniques are introduced, as they are central to the generalization. The comparison is made by overlaying the maps and observing the differences.

Chrisman (1989 page 522) suggests a strategy for measuring errors in categorical maps based upon the idea that error in categorical maps is the “deviation” between the representation of the reality reported in the map and the real scenario. This philosophy is an alternative to the stochastic modeling which, as reported by that author, simulates the real phenomena with numerical procedures derived from mathematical statistics. A simple principle is used: where two categorical maps “agree” the information they portray is considered reliable, where they “do not agree” the information is considered erroneous. The differences between the two maps may be due to errors in both or in one only. In general, when differences are discovered, it is necessary to decide which of the two maps is the most reliable before any attempt is made to correct them. The choice may be based upon personal
experience of who produced the maps, or personal knowledge of who is comparing the maps, using either the techniques used for map production or personal knowledge of the geographical area.

Once the reliability of the two maps is established, it is necessary to define the type of the expected error occurring in the map. The concept, and therefore the type of error depends on the discipline which produced or is using the map, for example, in photo-interpretation and remote sensing point sampling can be used to measure the accuracy of the classification. Errors in categorical maps are in the form of *polygons* and they may be of two different types commonly referred to as "positional" error and "attribute" error. A positional error is that spatial difference which is generated by a discrepancy in the location of a boundary between two categories. An attribute error is that spatial difference which shows lack of agreement between two maps in the classification of a certain area.

Positional and attribute errors, although theoretically well defined, are difficult to distinguish in practice. Strategies based upon geometric and attribute characteristics of polygons have been suggested in order to practically distinguish the two types of errors (Chrisman and Lester, 1991; Lester and Chrisman, 1991). For example the most common positional error in categorical maps gives rise to *sliver polygons* which are characterised by being "long and narrow". Spatial characteristics of polygons may be analysed in terms of mathematical formulae such as *compactness index*. The consequent evaluation of one or more indices allows the determination of the type of the error (Chrisman and Lester, 1991). Not all spatial characteristics are, however, meaningful for the recognition of both positional or attribute error. The compactness index, which measures the polygon shape from a ratio between the polygon's area and perimeter, is not sufficient to determine if a polygon is a sliver, in fact it may happen that a long and narrow polygon generates a compactness indices value similar to the value generated by a large (and therefore more compact) polygon (more details on compactness index may be found in Unwin, 1981 pages 201-204; Chrisman and Lester, 1991 page 335; Lester and Chrisman, 1991 page 649). The *perimeter index* (Chrisman and Lester, 1991; Lester and Chrisman, 1991) seems to be more appropriate for the recognition of sliver polygons, under the hypothesis that both source maps contribute equally to the polygon perimeter formation. In Fig. 6.2 the evaluation technique based upon the perimeter index is graphically represented.
Geometric Generalization

1. Map A  
2. Map B  
3. A+B  
4. sliver polygon

\[ P_{index} = \frac{a}{a+b} \]

where \( a \) is the contribution of the perimeter section of the object in the map A to the polygon (continuous line in 4.)

\( b \) is the contribution of the perimeter section of the object in the Map B to the polygon (dotted line in 4.)

The evaluation of \( P_{index} \) is:
IF \( P_{index} = 0.5 \)
THEN the polygon is a sliver

Fig. 6.2. Graphical representation of the \( P_{index} \) evaluation in recognising sliver polygons:
1.) Object under analysis represented in Map A., 2.) object under analysis represented in Map B, 3.) overlay of the two maps, and 4.) decomposition of difference, the sliver polygon.

This technique is used to recognise gradual change zones in this thesis. Gradual change zones are not however to be considered as errors (either positional or attribute) because they are generated by overlaying the closed boundary image on the classified image. The treatment of these zones should not be considered as a “boundary correction” (in fact none of the closed boundaries is moved or modified because the boundary location represented in the closed boundary map is considered “acceptable” for this thesis) but as a “contextual modification” of its content (compatibly to the surrounding context) in order to create the basis for an automatic performance of the consequent generalization activity.

This solution respects both sources of information, boundary distribution and thematic context, as independent and reliable information. The process responsible for the automatic recognition and treatment of gradual change zones is described in detail in the following section.
6.4 Automatic Recognition and Contextual Treatment of Gradual Change Zones

The process responsible for the automatic recognition and treatment of gradual change zones in the integrated image is a complex one as it must perform objective controls on each image-object in order to automatically detect, and then treat, those particular zones. These controls, both spatial and contextual, are performed in complete autonomy by the process in respect of the original image.

Gradual change zones are particularly clear along the boundaries of homogeneous objects, and for this reason the process treats the adjacents of all homogeneous image-objects containing one single class. When overlaying closed boundaries on a classified image, because of the noisy appearance of the raster image, it is difficult to find many objects containing one single class. In GIS applications involving land cover/land use data it is common for any polygon dominated by a single cover type (at least 90% of the polygon area) to be considered as being of that category. This is unlikely to be true in reality but is an acceptable cartographic approximation. In the context of the automatic generalization activity all those image-objects containing an image-class occupying of at least 90% of the object’s area are considered as containing uniquely that single class, later referred to as the unique image class.

An initial merging of adjacent image-objects containing the same single image-class is performed on the input image-objects prior to looking for gradual change zones, the result of this merging is shown in Fig. 6.3. The merging process is a central topic of the Spatial Generalization, and therefore it is described in detail in section 6.5.
Fig. 6.3. Result of the merging of adjacent image-objects containing the same single image-class performed on the image of atomic regions shown in Fig. 5.15. The merging is performed in order to prepare the basis on which to look for gradual change zones to treat for automatic generalization purposes.
The process responsible for the recognition of gradual change zones, if existing, and their contextual treatment is described below. The image-object representing the River Tejo in the image of objects is used. The process is illustrated by successive images giving a step-wise graphic representation of the entire process. The graphic step-wise representation of the process, has been directly produced by the automatic process, and was used (with others) as a test during the source code development.

For an image-object G to be considered as a gradual change zone it must satisfy the following conditions:

1. To be the adjacent of an object containing one single class (the unique image class), to be referred as the single-class object;
2. To contain an homogeneous, long and narrow region (the sliver polygon) lying parallel to the boundary section shared with the single-class object;
3. The sliver polygon is of the same theme as the single-class object; and
4. The class associated with the sliver polygon must be a minority in the object G.

The process is organised in 7 steps which are described separately in below:

1. Compatibility test;
2. Minority test;
3. Decomposition of the gradual change zone;
4. Deletion of isolated pixels within the gradual change zone;
5. Minimum surrounding box around the decomposed gradual change zone;
6. Evaluation of Perimeter Index; and
7. Contextual treatment of the thematic attributes of the gradual change zone.
6.4.1 Compatibility Test

Given the image-object $P_1$ containing one single image class $S_1$, each of its adjacents $P_n$ are analysed in order to determine if the adjacent contains the image-class $S_1$. Adjacents not containing the image class $S_1$ are not further analysed. The test is performed by examining the text file `polygon_class.dat`.

- IF $P_n$ is compatible with $P_1$
- THEN the search for sliver polygons may start
- ELSE do nothing

6.4.2 Minority Test

Given the image-object $P_1$ containing one single image-class $S_1$, for each compatible adjacent $P_n$, the corresponding shared boundary section between $P_1$ and $P_n$ is analysed mapping $P_n$ on the matrix of `_poly_info[]` structures (Fig. 6.4). Information is then extracted and stored in appropriate variables of `_poly_info[]` structures: `.direction`, `.sliver` and `.visited` (see section 4.4.1).

A logical test is applied to $P_n$ in order to establish the quantitative importance of the image class $S_1$ within the enclosed region, because the gradual change zone is expected to be a minority within the object. A minority class is a class which occupies less than half of the object area (Fig. 6.5). The adjacents containing percentages of area occupied by image class $S_1$ not satisfying the threshold are not analysed further.
Fig. 6.4. This is an adjacent of the river object. This adjacent (later referred to as the adjacent object) is represented in the figure as it is stored by the process in the variable `filled` of the matrix of `_poly_info[]` structures (pixel 1 for boundary, pixel 2 for the object's enclosed area). The adjacent object is taken as an example in this chapter to explain the performance of the process.
Fig. 6.5. The thematic attributes of the adjacent object are graphically represented as they are stored in the variable .gen_value in the structure poly_info[].
6.4.3 Decomposition of Differences

Given the image-object $P_i$ containing the unique image-class $S_i$, for each pixel belonging to the shared boundary section, the corresponding 4-connected neighbourhood is examined in order to:

I. Define the initial set of pixels associated with class $S_i$ (i.e. belonging to the potential gradual change zone) along the shared boundary section in the 4 directions: north, south, east or west;

II. Establish the direction in which the gradual change zone extends from the shared boundary section; and

III. Generate a zone-segment in the direction associated with the gradual change zone for each pixel in the set of initial pixels.

The process analyses the shared boundary section pixel-by-pixel and the 4-connected neighbourhood associated with each shared boundary pixel, determining the direction of the potential gradual change zone. The direction depends on the orientation of the shared boundary section and on which side of the shared boundary the adjacent is placed. Thus, if the shared boundary is extending from “north to south” and the adjacent under analysis is on the “west” of the shared boundary, then the gradual change zone is searched from the “east” to the “west”.

Once the direction of the gradual change zone is fixed, for each pixel in the initial set of pixels set to class $S_i$, the process reads the matrix of _poly_info{} structures in order to find continuous pixels set to class $S_i$ in the appropriate direction, forming zone-segments. Each zone-segment is delimited by one of the pixels in the initial set and by an ending extreme coinciding with the first set of pixels (internal to the adjacent) of an image class which is not $S_i$ encountered in the gradual change zone direction, as shown in Fig. 6.6 and Fig. 6.7.
Fig. 6.6. The spatial decomposition of differences generated by the overlay of the closed boundary image onto the classified image. Zone-segments of a potential gradual change zone are detected in the west direction of the boundary section shared by the adjacent object and the "water-object". Pixels labeled as 3 belong to the shared boundary section, and pixels labeled as 4 form the internal boundary of the potential gradual change zone.
Fig. 6.7. The decomposed differences detected in the adjacent object.
6.4.4 Deletion of Isolated Sliver Pixels

Isolated pixels (in the initial set of pixels) set to image class $S_i$ are rejected from the process as shown in Fig. 6.8. In the context of this thesis, an isolated pixel of class $S_i$ does not satisfy on its own the spatial and attribute characteristics of a gradual change zone, and is considered as noise in the classified image.

Fig. 6.8. Isolated "water" pixels occurring in the adjacent object are not considered during processing because they do not satisfy the defined characteristics of being a gradual change zone.
6.4.5 Minimum Surrounding Box around the Gradual Change Zone

Once all zone-segments have been extracted from the internal region associated with the adjacent object, a minimum surrounding box around the perimeter of the area extracted is fixed, forming the boundary of the potential gradual change zone, as shown in Fig. 6.9.

Fig. 6.9. The minimum surrounding box around the potential gradual change zone, detected by the process.
6.4.6 Evaluation of Perimeter Index \( P_{index} \)

As shown in Fig. 6.9, the boundary of the potential gradual change zone is formed by two groups of pixels: a) a group set to 3 and b) a group set to 4. In terms of sliver polygons as described in section 6.2, pixels set to 3 represent the contribution of object \( P_i \) to the boundary of the gradual change zone, and pixels set to 4 represent the contribution of the adjacent object to the boundary of the gradual change zone. The perimeter index, \( P_{index} \) (section 6.2 page 132) associated with the polygon representing the gradual change zone (Fig. 6.9) is calculated as following:

\[
P_{index} = \frac{la}{la+lb}
\]

where \( la \) is the number of pixels set to 3, and \( lb \) is the number of pixels set to 4.

To be considered a gradual change zone, the \( P_{index} \) must be within the exclusive range (0.4, 0.6). As highlighted in (Chrisman and Lester, 1991) the Perimeter index can be calculated with either map as source A. Comparing the two Perimeter index versions the two results are symmetric around 0.5.

In the example used in this section to graphically represent the process performance, referring to Fig. 6.9 the potential gradual change zone extracted from the adjacent of the image-object representing the River Tejo, is calculated as follows, where source A is the river object and source B is the adjacent (represented in Fig. 6.9):

\[
la = 29 \text{ (pixels)} \quad lb = 31 \text{ (pixels)} \quad P_{index} = \frac{29}{29+31} = 0.48
\]

Exchanging the two sources where source A is the adjacent and source B is the river object, \( P_{index} \) is calculated as follows:

\[
la = 31 \text{ (pixels)} \quad lb = 29 \text{ (pixels)} \quad P_{index} = \frac{31}{31+29} = 0.52
\]
The two Pindex versions are both symmetric around 0.5 (-0.02, +0.02) and falling in the range (0.4, 0.6) therefore the extracted area within the adjacent object is a gradual change zone.

6.4.7 Contextual Treatment of the Gradual Change Zone

The contextual treatment of the thematic attributes of the gradual change zone is performed in two steps. The first step of the treatment replaces, segment-by-segment, the image-class $S_i$ with the image-class associated with the ending extreme of the particular zone-segment (section 6.4.3). If a zone-segment has an ending extreme coinciding with the boundary of the adjacent object, no replacement is performed for the moment (Fig. 6.10).

The second iterative stage of treatment is then activated in order to replace those zone-segments not treated in the previous stage. All pixels belonging to zone-segments are iteratively analysed and, if it is the case, modified. If an image-class different from $S_i$ occurs in the neighbourhood of the particular segment’s pixel, then the segment’s pixel is set to this image class. If no other image classes occur in the neighbourhood, the segment’s pixel is momentarily left as it is, and another segment’s pixel is analysed. The dynamic treatment goes on until no more segment’s pixels are in the gradual change zone (Fig. 6.11).

The association when possible of an entire zone-segment with the image class spatially closer to the segment in the segment direction generally allows a more homogeneous distribution of image-classes within the gradual change zone, contributing to the generalization process. If only the second technique of per-pixel treatment was used, a random iterative replacement of image classes would certainly be more fragmented. Further, the adopted strategy respects the requirement of objective treatment in an automatic environment when no user interaction is allowed and it respects the original distribution of image-classes.
Fig. 6.10. The result of the first step of the contextual treatment of the attributes of the gradual change zone detected in the adjacent object.
Fig. 6.11. The result of the second (final) step of the contextual treatment of the attributes of the gradual change zone detected in the adjacent object.
6.4.8 Results of the Automatic Recognition and Treatment of Gradual Change Zones

The final output of the process applied to the entire input image is shown in Fig. 6.12. In this section the evaluation of the results obtained by the contextual treatment of attribute characteristics of gradual change zones is presented and divided into two main tasks: a) the initial merging activity, and b) the detection of gradual change zones and their treatment.

Visually comparing input and output images, the reduction of boundaries performed by the initial merging activity is evident. Errors are observed in the form of shared boundary sections not completely removed. These errors derive from the incomplete series of spatial controls of TempProc() procedure responsible for the deletion of shared boundary section (described in the following sections), and may also derive from errors in the segmented image. The controls performed by TempProc() are computationally complex and not easy to design a priori. The result is that the collection of controls embedded in the current version of the source code are not sufficient to cover the unpredictable large number of spatial combination of pixels in an “anonymous” boundary. Details on the specific algorithms and corresponding source code responsible for the merging activity are given in section 6.5.

Visual inspection of the input and output images gives rise to comments and conclusions on the performance of the gradual change zones detection and treatment. Gradual change zones have been modified respecting the image context. Focusing on the object associated with the River Tejo, gradual change zones on the western River edge have been clearly eliminated. Few small objects (also adjacent to the River western edge) containing the image-class ‘water’ have been preserved by the process as not satisfying the characteristics, defined in the context of this thesis (page 139), of a gradual change zones.
Fig. 6.12. Results of the Automatic Statistical Pre-Processing of Image-Objects.
6.5 Spatial Generalization

The Spatial Generalization process consists of an iterative rule-based polygon merging activity conducted on the input image-objects in order to form regional boundaries, called polygons. The method consists of iteratively deleting shared boundary sections of compatible pairs of adjacent objects forming new larger objects.

The merging process is guided by three rules and one constraint on compatibility among image-classes between two adjacent objects which are candidates for merging. One or more pairs of adjacents are merged at each iteration. After each iteration a new image of objects is produced, new and old objects are newly described, and the state of adjacency among new and old objects is recalculated. This information is the input for the subsequent iteration. No priority among image-classes is established to guide the merging. A constraint on ‘water’ objects is foreseen by which they may be merged only to other ‘water’ objects.

Each rule is iteratively applied to the entire group of image-objects until no objects satisfying the rule exist in the image. The process stops when no more image-objects satisfy the last applied rule.

6.5.1. Compatibility among groups of Image-classes

Each image-object contains an original set of image-classes, derived from the overlay of original closed boundaries on the geographically corresponding classified image. The thematic content of each image-object is still “unprocessed” for generalization purposes, and is characterised by “scattered and noisy” appearance or by “misclassifications”. Therefore the original spatial distribution of pixel values within each closed boundary cannot be the essential characteristic for object categorization in the generalization context. On the contrary, the nominal thematic pattern, i.e. the list of image-classes occurring in the object, and the population statistics, i.e. the occurrence of the number of pixels of each image-class within the object, can be essential characteristics for the categorization of objects.

For example, a “urban” object in a generalized map is associated to spectral themes such as: “houses”, “concrete”, “grass”, “roads” and to specific ranges of population statistics, such as a high occurrence of “houses”, “concrete” and “roads” and a low occurrence of “grass”. Each object containing all these themes with population statistics satisfying the pre-defined
ranges of themes occurrence, is classified as “urban” independently of the distribution of
themes within the object.

At this stage of processing, the compatibility among image-classes of two adjacent
objects is automatically performed and is established as following:

Given \((P_1, P_2)\) a pair of adjacent objects, \(\{s_1\}\) and \(\{s_2\}\) the sets of image-classes
respectively associated to \(P_1\) and \(P_2\), and \(S = \{c_1, c_2, c_3, c_4, c_5, c_6, c_7, c_8, c_9, c_{10}\}\) the set of all
image-classes in the classification scheme:

\[
\text{IF } \{s_2\} \text{ is a subset of } \{s_1\} \text{ OR } \{s_1\} \text{ is a subset of } \{s_2\} \text{ OR } \{s_1\} \text{ is equal to } \{s_2\} \\
\text{THEN } P_1 \text{ and } P_2 \text{ are compatible} \\
\text{ELSE } P_1 \text{ and } P_2 \text{ are not compatible}
\]

example_1: \(s_1 = \{c_1, c_3, c_3, c_7\}, \quad s_2 = \{c_3, c_3\} \quad P_2 \text{ is compatible to } P_1\)
example_2: \(s_1 = \{c_1, c_3, c_5, c_7\}, \quad s_2 = \{c_2, c_3, c_5, c_7\} \quad P_2 \text{ is not compatible to } P_1\)
example_3: \(s_1 = \{c_1, c_3, c_5, c_7\}, \quad s_2 = \{c_2, c_4, c_6, c_8, c_{10}\} \quad P_2 \text{ is not compatible to } P_1\)

6.5.2. The Merging Rules

Name: \textit{First Merging Rule}

Description: Merging of pairs of adjacent objects containing the same single image-class.

Explanation: One image-class is analysed at a time. For each image-object containing as a
unique image-class (definition at page 133) the current image-class the most
convenient adjacent is chosen for the merge. In case of ties, i.e. in the case that
two or more adjacents contain that unique image-class, the \textit{largest} adjacent is
taken for merging. The process stops when no more pairs of adjacents satisfying
the rule are found.

Rule: Given \(S = \{c_1, c_2, c_3, c_4, c_5, c_6, c_7, c_8, c_9, c_{10}\}\) the set of image-classes associated with
the classification scheme, \(c_n\) is the image-class currently under analysis, \(P_1\) an image-
object containing \(c_n\) as unique image-class, \(P_2\) one of the adjacents of object \(P_1\), and \(\{s_2\}\)
is the set of image-classes associated with the adjacent \(P_2\):

\[
\text{IF } \{s_2\} \text{ contains } c_n \\
\text{THEN } P_1 \text{ is merged to } P_2 \\
\text{ELSE } P_1 \text{ is not merged to } P_2
\]
Name:       \textit{TP\_Merging\_Rule}

Description: Merging of "small" image-objects to the most compatible of their adjacents.

Explanation: The \textit{threshold on perimeter length} \textit{TP} of 50 pixels is applied to each image-object. For each image-object satisfying the threshold, the most compatible adjacent is taken for merging. In case of ties, the \textit{largest} adjacent is taken for merging. When no more image-objects with perimeter length less than the TP threshold are found, the process stops.

The threshold on perimeter length has been chosen instead of a threshold on area since considering the input closed boundary map and the geometric description of each closed boundary as per-pixel raster co-ordinates, a threshold on perimeter length allows the application of generalization such as the merging of adjacent closed boundaries, without the need of any further calculation.

The choice of \textit{TP} = 50 pixels comes from the evaluation of the range of values corresponding to the perimeter length of atomic regions in the input closed boundary map. The shortest perimeter length was 3 pixels, the longest perimeter length was 409 pixels (corresponding to the object associated to the River Tejo), and the average of perimeter length of the majority of the occurring image-objects was around 100 pixels. The elimination of all objects smaller than 50 pixels in perimeter length, makes the range of perimeter length of the occurring objects more homogeneous.

The threshold \textit{TP} of 50 pixels has then been compared with the minimum mapping unit of 25 hectares of CORINE maps. A circumference with area equal to 25 hectares has been chosen to model the CORINE minimum mapping unit.

The following calculations have then been made to calculate the number of 30 metres pixels corresponding with the perimeter of that circumference:

\begin{align*}
\text{Area} &= 25 \text{ hectares} = 2.5 \times 10^5 \text{ m}^2 \\
\text{Circumference Area} &= \pi r^2 \\
\text{Circumference Perimeter} &= 2 \pi r \\
r &= [(2.5 \times 10^5) / \pi]^{1/2} \approx 282 \text{ metres} \\
\text{Perimeter} &= 2 \pi \times 282 \approx 1772 \text{ metres} \\
\text{Number of 30 m. pixels} &= 1772 / 30 \approx 59 \text{ pixels}
\end{align*}
Rule: Given $P_1$ an image-object of $P_n$ perimeter size:

\[
\text{IF } P_n < TP \\
\text{THEN the most compatible adjacent } a_i \text{ of } P_1 \text{ is selected and the pair } (P_1, a_i) \text{ becomes a candidate for merging in the current iteration} \\
\text{ELSE } P_1, \text{ satisfying the threshold, is not further analysed}
\]

Name: \textit{TG\textunderscore Merging\textunderscore Rule}

Description: Merging of compatible adjacents separated by "weak" shared boundary sections.

Explanation: Not all the shared boundary sections are in origin equally strong. For each shared boundary section the value $agv$ is calculated as the average of the sum of original gradient values of each pixel belonging to the shared boundary section, i.e. original radiance pixel values defined by the SED algorithm (section 4.3) and used in combination with thresholds and filtering to create the closed boundaries. The \textit{threshold on boundary strength} $TG$ is then automatically calculated as the average of all $agv$ values calculated in the image. All shared boundaries are analysed, those shared boundaries not satisfying the $TG$ threshold and formed by the adjacency of two compatible image-objects are eliminated. When no more shared boundary sections weaker than the $TG$ threshold are found, the process stops.

Rule: Given the pair of adjacents, compatible image-objects $(P_1, P_2)$ and $agv$ the strength of the boundary section shared by the pair:

\[
\text{IF } agv < TG \\
\text{THEN the pair } (P_1, P_2) \text{ becomes a candidate for merging in the current iteration} \\
\text{ELSE the pair } (P_1, P_2) \text{ satisfying the threshold is not further analysed}
\]

6.5.3 \textit{Multi-candidate Merging}

The merging process automatically selects the candidates for merging at each iteration via the access to the text files \textit{comparison.dat} and \textit{polygon\_class.dat}. At each iteration the process selects (from the list of candidates selected for that particular iteration) and merges all
pairs of adjacents which are not multiple-adjacents. Multiple-adjacent pairs of image-objects are ignored by the process in the current iteration. After the merging of all selected pairs of adjacents, the process updates the text information concerning the image-objects with the new information and re-sets the basis for the consequent iteration and multiple merging.

The dynamic data structure _stack_borders{} supports the multi-candidates merging in the selection of pairs of adjacent objects which are not multiple-adjacents. The _stack_borders{} is an array of elements allocated when necessary during the execution of the process. At each iteration this array collects information concerning each shared boundary section formed by the pairs of objects automatically selected as satisfying the currently applied rule. The declaration of the structure _stack_borders{} in the source code in C language is:

```c
_stack_borders{
    int p1;
    int p2;
    int length;
    int strength;
    int *x_coord;
    int *y_coord;
    int ch;
}
```

Each element in the stack collects information concerning one single pair of objects, thus the generic element n in the stack contains the following information:

- Elements p1 and p2 store the identifiers of two adjacent objects;
- Element length stores the extension in no. of pixels of the boundary section shared by p1 and p2;
- Element strength stores the avg value associated to the boundary section shared by p1 and p2 and represents the strength of the boundary section;
- Elements *x_coord and *y_coord store respectively the (x, y) raster co-ordinates of each pixel belonging to the boundary section shared by p1 and p2 (the process dynamically allocates the appropriate number of elements corresponding to the length of the shared boundary section); and
• Element \( ch \) is a control variable which if set to 0 indicates that the pair \((p_1, p_2)\) can be merged in the current iteration, or if it is set to -1 indicates that the pair \((p_1, p_2)\) cannot be merged in the current iteration.

The use of the stack \_stackBorders[]\) is essential to reduce the execution time of the merging process. The most expensive activity during the merging process is updating the information concerning newly formed and old image-objects after each iteration performed by the procedures \texttt{RAGalgorithm()}, \texttt{FindIntExtPoly()} and \texttt{PolygonEdgeDescription()} (chapter 5). In the case of serial computing, if at each iteration only one single pair of adjacents is merged, the entire procedure may last for weeks. This was confirmed by applying the \texttt{First_Merging_Rule} during the error polygons detection without the application of the stack. The \texttt{First_Merging_Rule} reduced the image from 2032 polygons down to 1570 in 4 days working 24 hours per-day.

The use of the stack \_stackBorders[]\) allows a parallel merging of several pairs of adjacents at each iteration optimising the calls to the updating procedure. This was also confirmed by running again the process associated to the \texttt{First_Merging_Rule}, which then took only a few hours to complete.

The method used for the parallel merging using the stack \_stackBorders[]\) consists of several controls performed by the process to eliminate from the list of candidates for merging multiple-adjacent pairs of image-objects as described below:

1. Palindromes of pairs of objects are detected in the \_stackBorders[]\) list, for example the pair \((4, 7)\) and the pair \((7, 4)\) represent the same shared boundary section;
2. Only one palindrome is maintained in the \_stackBorders[]\) list, for example only the pair \((4, 7)\);
3. The multiple-adjacency is then checked among all the remaining pairs of objects, for example the pairs \((4, 7)\), \((4, 50)\), \((71, 4)\) and \((99, 4)\) are all multiple-adjacent pairs, in fact objects 7, 50, 71 and 99 are all adjacents of the same object 4;
4. For each group of multiple-adjacents only one pair is kept in the \_stackBorders[]\) list, for example \((4, 7)\); and
5. The \_stackBorders[]\) list finally contains spatially independent pairs of objects which are merged in the current iteration.
6.5.4 Automatic Deletion of Shared Boundary Sections

Essential for the execution of the process concerning the automatic deletion of the boundary section shared by two adjacent objects selected for the merging is the matrix of _poly_info{} structures mentioned several times in chapter 5. In each iteration, one pair \((p_1, p_2)\) of objects is merged at a time. The matrix of _poly_info{} structures is used to map both objects \(p_1\) and \(p_2\) in order to isolate the shared boundary section and to delete it, forming a new closed boundary to describe the newly formed (larger) object.

Once the objects \(p_1\) and \(p_2\) are mapped in the matrix, and the shared boundary section has been isolated, as graphically represented in Fig. 6.13a, the procedure TempProc() responsible for the effective erasure activity is activated. TempProc() is a primitive IF-THEN-ELSE procedure checking the 4-connected neighbourhood of each pixel belonging to the shared boundary section, in order to adequately delete pixel-by-pixel the boundary section. TempProc() foresees a set of spatial templates representing combinations of boundary pixels in a 4-connected neighbourhood.

![Fig. 6.13a. Isolation of the shared boundary section as performed in the matrix of _poly_info structures. Pixels set to 3 are shared boundary pixels.](image)

\[
\begin{array}{cccccc}
1 & 1 & 1 & 4 & 4 & 4 \\
1 & 3 & 3 & 4 & 4 & 4 \\
1 & 3 & 3 & 4 & 4 & 4 \\
1 & 3 & 3 & 4 & 4 & 4 \\
1 & 1 & 1 & 4 & 4 & 4 \\
\end{array}
\]

TempProc() compares the state of the 4-connected neighbourhood of one pixel of the shared boundary section at a time with the a-priori defined spatial templates, the entire list of templates is given in Appendix B.
The 4-connected neighbourhood of a pixel belonging to a shared boundary section, is extracted applying the mask centered on the pixel under analysis.

The 4 neighbours of the pixel P are visited in the order 1, 2, 3, 4 as depicted in the mask.

The information necessary for the deleting activity, collected iteratively by the 4-connected neighbourhood, are the values reported in the matrix of _poly_info[] structures by the variable filled as shown in Fig. 6.13.

TempProc() extracts the values of each 4-connected neighbourhood of one boundary pixel and directly compares it with the pre-defined list of templates. If the template is found in the list, then the boundary pixel under analysis is immediately deleted by setting it to 2 in the variable filled of the corresponding entry in the matrix of _poly_info[] structures. In the context of Fig. 6.13 the procedure TempProc() works in 5 iterations, which are graphically simulated below, another example of deleting a shared boundary section is given in Fig. 6.14:

Iteration 1: the 4-connected mask is applied to the first pixel belonging to the shared boundary section, and the corresponding neighbourhood is extracted.

```
1 1 1 1 4 4 4 4 4
1 1 3 4
1 3 4
1 3 4
1 1 3 4
1 1 1 1 4 4 4 4 4
```

The neighbourhood above is not included in the list of pre-defined templates, therefore the boundary pixel under analysis is not deleted.

Iteration 2: the 4-connected mask is applied to the second pixel belonging to the shared boundary section, and the corresponding neighbourhood is extracted.

```
1 1 1 4 4 4 4 4
1 3 4
1 3 4
1 - 3 4
1 3 4
1 1 1 1 4 4 4 4 4
```

The neighbourhood above is included in the list of pre-defined templates, therefore the boundary pixel under analysis is deleted.
Iteration 3: the 4-connected mask is applied to the third pixel belonging to the shared boundary section, and the corresponding neighbourhood is extracted.

\[
\begin{array}{cccccc}
1 & 1 & 1 & 1 & 4 & 4 \\
1 & 3 & 4 \\
1 & 4 \\
1 & 4 \\
1 & 4 \\
1 & 4 & 4 & 4 & 4 \\
\end{array}
\]

The neighbourhood above is included in the list of pre-defined templates, therefore the boundary pixel under analysis is deleted.

Iteration 4: the 4-connected mask is applied to the fourth pixel belonging to the shared boundary section, and the corresponding neighbourhood is extracted.

\[
\begin{array}{cccccc}
1 & 1 & 1 & 1 & 4 & 4 \\
1 & 3 & 4 \\
1 & 4 \\
1 & 4 \\
1 & 4 \\
1 & 4 & 4 & 4 & 4 \\
\end{array}
\]

The neighbourhood above is not included in the list of pre-defined templates, therefore the boundary pixel under analysis is not deleted.

Iteration 5: each boundary pixel labeled as 3 and 4 in the matrix of _poly_info{} structures are set to 1 in the variable .filled forming the new closed boundary of the newly generated image-object as shown in Fig. 6.13b:

\[
\begin{array}{cccccccc}
1 & 1 & 1 & 1 & 1 & 1 & 1 & 1 \\
1 & 1 & 1 & 1 & 1 & 1 & 1 & 1 \\
1 & 1 & 1 & 1 & 1 & 1 & 1 & 1 \\
1 & 1 & 1 & 1 & 1 & 1 & 1 & 1 \\
1 & 1 & 1 & 1 & 1 & 1 & 1 & 1 \\
1 & 1 & 1 & 1 & 1 & 1 & 1 & 1 \\
1 & 1 & 1 & 1 & 1 & 1 & 1 & 1 \\
\end{array}
\]

Fig. 6.13b. New object formed by the merging of the two independent adjacent objects shown in Fig. 6.13a.
6.5.5 Results of the Spatial Generalization

The aim of the Spatial Generalization is to reduce the spatial complexity of closed boundaries in order to create main regional boundaries, i.e. main polygons. The automatic rule-based polygon merging while aggregating adjacent image-objects simplified the appearance of the closed boundaries image, reducing the number of boundaries. Quantitatively, the merging process reduced the number of objects in the image from the initial 2032 atomic regions, shown in Fig. 6.2, to the final 171 main polygons in the output image. More precisely, First_Merging_Rule, applied twice, produced an image of 1570 closed boundaries, TP_Merging_Rule (applied to the output image of the First_Merging_Rule) produced an image of 223 closed boundaries, and TG_Merging_Rule (applied to the output image of the TP_Merging_Rule) produced an image of 171 closed boundaries, as shown in Figures 6.15, 6.16 and 6.17.

From the analysis of the images produced at each stage of the merging activity, represented in Figures 6.18, 6.19 and 6.20, one notes a precise aggregation of objects consistent with the thematic and spatial context of the original regions distribution. A few spatial errors may be clearly observed in Figures 6.15 to 6.17 (and Figures 6.18 to 6.20) in the form of shared boundary pixels not deleted by the competent process. As explained in section 6.5.4 the procedure TempProc() is based on a-priori defined combinations of 4-connected shared boundary pixels of hypothetical boundaries. Therefore, TempProc() may not cover all the possibility of boundary pixels combinations in a 4-connected neighbourhood, and requires
a further revision of the source code to eliminate the propagation of errors. In fact, being a problem of "combination" of elements in a fixed neighbourhood space, the a-priori defined list of 4-connected pixels combinations is formed by a "finite" number of elements (although large) and an automatic algorithm calculating this finite number of combination may be designed.

Fig. 6.15 The closed boundary map after the application of the First Merging Rule() process to the input image of 2032. The new closed boundary map contains 1570 closed boundaries.
Fig. 6.16. The closed boundary map after the application of the TP_Merging_Rule() process to the image of 1570. The new closed boundary map contains 223 closed boundaries.
Fig. 6.17. The closed boundary map after the application of the *TG_Merging_Rule()* process to the image of 223. The new closed boundary map contains 171 closed boundaries.
Fig. 6.18. The classified image after the application of the First Merging Rule process, containing 1570 image-objects.
Fig. 6.19. The product shown in Fig. 6.18, after the application of TP_Merging_Rule(), which contains 223 image-objects.
Fig. 6.20. The product shown in Fig. 6.19, after the application of the TG_Merging_Rule0, which contains 171 image-objects.
6.6 Thematic Smoothing

The Thematic Smoothing, as designed and developed for this thesis, consists of an automatic simplification of thematic complexity in the image performed independently within each main regional boundary, i.e. main polygons created by the Spatial Generalization. The smoothing process is based on the principles of the Majority Filtering and the Region Growing techniques, although modified in order to work within each polygon as explained in section 3.3. The smoothing process maps one polygon at a time on the matrix of _poly_info[] structures and analyses the population statistics in order to simplify the polygon's content consistently to the natural distribution of image-classes. Two activities are involved in the thematic simplification: 1) a Polygon Majority Class Smoothing and 2) a Polygon Reduced Classes Growing which are described in the following sections.

6.6.1 Per-polygon Majority Class Smoothing

For each polygon in the image, the process examines the "thematic population" statistics which are calculated as the frequency, in number of pixels, occurring within the polygon for each image-class. The frequency of each image-class is then stored in the array inclassfreq[] which is used during the entire execution of the process, as in the example below:

\[ \text{inclassfreq}[3] = 10 \]

which means that the image-class 3 has a frequency of 10 pixels within the polygon.

Analysing the array inclassfreq[] the process defines which is the "majority class" for the polygon under analysis as the image-class most frequently occurring within the polygon. The process then associates the majority class to the entire polygon setting the variable .gen_value in the matrix of _poly_info[] structures to the majority class for all the pixels belonging to the region enclosed by the polygon boundary.

6.6.2 Per-polygon Reduced Class Growing

For each minor image-class occurring in the polygon substituted by the majority class during the smoothing process, a threshold on percentage is automatically calculated for the polygon under analysis. The threshold is calculated by dividing the area associated with all minor classes with the number of minor classes as described below:

\[ \text{percentage} = \left( \frac{\text{tot}_\text{pixels} - \text{frequency[majority_class]}}{\text{tot}_\text{classes} - 1} \right) + 1 \]
Logically the *percentage* value represents the case in which all minor classes are *equally important* occupying an *equal percentage of area*. The addition of 1 to the percentage value is for rounding.

All minor classes having *frequency greater than* the threshold are considered important information and must be spatially re-introduced in the polygon. All minor classes having *frequency less than* the threshold are considered minor information and are permanently eliminated from the thematic attributes of the polygon.

All the minor classes selected as important information, are re-introduced one at a time by the competent process starting from the most predominant. The method of re-population of an image-class consists in automatically detecting the largest and most homogeneous cluster of the minor class within the polygon and to concentrate the re-population of the minor class in that area. The cluster is then re-introduced in the matrix and pixel-by-pixel extended to pixels directly connected to the cluster which was originally set to the minor class.

Each polygon is analysed independently from the others, and one at a time is mapped in the matrix of `_poly_info[]` structures. The process uses a 3x3 moving window applied to each pixel in the matrix of `_poly_info[]` structures corresponding to the region enclosed by the polygon's boundary. For each pixel set to the minor class which is currently being re-populated, the process analyses the 3x3 neighbourhood counting the number of neighbours set to the central pixel class and stores the information in the variable `.growing` corresponding to the central pixel in the matrix of `_poly_info[]` structures. The variable may vary in the range of integers [0, 8], being the entries in the 3x3 window. A value in the range of [5, 8] represents the existence of a large cluster centered in the central pixel of the moving window. A value of 8 represents the existence of a compact and homogeneous cluster centered in the central pixel of the moving window.

Iteratively the process checks the value of the variable `.growing` in the matrix for all the pixels set to the minor class currently under analysis, and at each iteration chooses the pixel (or the pixels) with the highest `.growing` value, i.e. chooses the largest cluster (or clusters). The process then re-introduces each pixel belonging to the cluster back in the matrix. One or more clusters formed by an equal number of pixels may be extracted in the same iteration and the process equally re-introduces them in the same iteration. At each iteration the process recalculates the `.growing` value for each pixel set to the minor class excluding the central pixels.
of clusters already introduced, and selects a new cluster (or clusters) to be re-introduced in the matrix.

The maximum number of pixels, stored in the variable \( \text{rest}_\text{to}_\text{introduce} \), to be re-introduced for each minor class selected for re-population corresponds to the frequency of that class, and after each iteration the variable \( \text{rest}_\text{to}_\text{introduce} \) is reduced by the number of pixels put back in the matrix. Until \( \text{rest}_\text{to}_\text{introduce} \) is greater than 0 and until pixels with \( \text{growing} \) value in the range \([5, 8]\) exist, the minor class is processed for re-population extending pixel-by-pixel the re-introduced cluster (or clusters) looking for pixels directly connected to the cluster (or clusters) and originally set to the minor class.

In general, not all the original population is re-introduced due to the typical "salt'n'pepper" appearance of classified images which does not form many homogeneous and compact clusters, and due to the fact that the process does not allow any minor class to occupy locations originally occupied by other minor classes.

This strategy attempts to preserve the distribution of natural regions. Further this strategy ensures an objective selection of geographical information to be maintained in the final generalized product by evaluating also the qualitative importance. In fact, a minor class with a relatively high frequency but spatially distributed as many clusters of maximum 2, 3 pixels in the polygon is not re-populated because it is not sufficiently compact.

The fixed size 3x3 for the moving window has been chosen as a suitable compromise to combine the necessity of a parameter to qualitatively measure the distribution of a minor class with fundamental characteristics of themes distribution in classified images and the irregular (and often non compact) shape of polygons automatically detected by segmentation algorithms.

### 6.6.3 Results of the Thematic Smoothing

The Smoothing algorithm has been applied to the main regional boundaries produced by the Spatial Generalization. To test the efficiency of the algorithm two different products derived by the Spatial Generalization have been used: a) the image of 223 image-objects and b) the image of 171 image-objects which are illustrated in section 6.5.5.

The procedure \( \text{FindIntExtPoly}() \) (section 5.3.1) is essential to the process for the mapping of each main polygon during the smoothing treatment. The incompleteness of the list
of pre-defined templates (listed in Appendix I) used by the procedure \textit{FindIntExtPoly()}, as explained in section 5.3, to distinguish between internal and external segments of one polygon's region, does not allow the process to recognise completely the region of some polygons. This causes the generation of black areas occurring in the smoothed products shown in this section, which are not "recognised" by the process as belonging to any image-object. As explained in section 6.5.5 a further revision of the source code and the creation of a computing algorithm able to calculate all possible combinations of templates listed in Appendix A, certainly will avoid this type of error.

The image of 223 objects and the smoothed product, referred to as product A, are shown in Figures 6.16 and 6.21. Comparing the two images it may be observed that:

1. The thematic content of the image has been clearly simplified respecting the natural distribution of quantitatively important regions; and
2. The re-population of quantitative and qualitative important information has been emphasised in the original location.

The image of 171 objects and the smoothed product, referred as product B, are shown in Figures 6.17 and 6.22. These results are similar to the results described for product A. It may be concluded that the process while working on a per-object basis is consistent to the entire image context.

Comparing the two smoothed products, the most evident difference is the increase, in image B, of the area occupied by the image-class "grass" (green) after generalization, which distinctly assumes the role of the background theme in the thematic context of the image. The most significant information, such as land cover "urban" areas (grey), "forest" (orange) and "horticulture" (red), already emphasised in image A, have been spatially emphasised in image B since larger regional boundaries are available, but always in locations where the themes were originally predominant.

In the context of the entire image, although homogeneously distributed the "vineyards" regions are not quantitatively important, with respect to other land cover classes in the image. However, the Smoothing process preserved "vineyards" regions in their original locations since they represent qualitatively important information.
Fig. 6.21 The image of 223 image-objects simplified by the Smoothing Process
Fig. 6.22. The image of 171 image-objects simplified by the Smoothing Process
6.7 Summary of the Geometric Generalization Process

The generalization process developed during this thesis is objective and consistent with the input classified image, performing its activity independently of the type of input data. It may be concluded that the minimum essential characteristics of such a process are:

1. Acceptance of any spectral land cover classification scheme;
2. Consistency to the input thematic context;
3. Anonymous treatment of each class by its numerical value; and
4. Equal treatment for each class, no priority among classes is established.

From the analysis of the technical characteristics and performance of the Automatic Contextual Pre-processing of Image-Objects it may be concluded that when combining or integrating a classified image and a segmented image both representing an identical geographic scenario:

1. The detection of gradual change zones is essential to avoid the introduction of spatial errors during the generalization;
2. Modeling gradual change zones as sliver polygons is appropriate for automatic processing. These particular sliver polygons must be corrected in their thematic content not in their spatial displacement;
3. The step-wise process responsible for the contextual recognition and treatment of gradual change zones is characterised by:
   • consistency to the original spatial distribution of thematic regions and proportion;
   • objectivity of performance.

The Rule-Based Polygon Merging process is organised in three sequential production rules which may be considered the minimum and essential constraints for an automatic and a powerful merging activity. A constraint on thematic compatibility among adjacent image-objects (the thematic context) has been used in combination with the three rules, First_Rule, TP_Rule and TG_Rule.
The strategy adopted for the automatic merging of image-objects has been shown to be successful:

1. **Quantitatively** in reducing spatial (boundary) information;
2. **Qualitatively** in accurate aggregation of image-objects consistent to the thematic and spatial context of the original regions distribution;
3. **Technically** in the combination of rules and thematic compatibility constraints which is an appropriate, but objective, simulator of human expert judgement in selecting the most compatible pairs of adjacent objects to merge at each iteration; and
4. **Technically** in the computation of the rules and of the thematic compatibility constraint which is appropriate for automatic and unsupervised execution.

The thematic smoothing algorithm created to simplify the thematic content of each image-object in the image, is based on a *per-object strategy* which extracts the required information dynamically and directly from the available data sets, and is consistent with the input spatial detail. The smoothing algorithm combines the modified versions of traditional Iterative Majority Filtering (IMF) and Iterative Reduced Class Growing (IRCG) algorithms adapted from a per-pixel to a per-object performance for which no iterations nor moving windows are allowed. The algorithm is also *independent* of the image-object *shape, size* and *content* being thus:

1. Powerful in smoothing;
2. Consistent with the original context of each image-object;
3. Objective and generally applicable; and
4. Suitable for automatic and unsupervised processing;

The process also establishes the *quantitative importance of each minor class* within a given image-object based on a threshold on percentage of frequency, dynamically calculated for each image-object. Thus one minor class may be cancelled from a particular image-object but may be maintained in another one, giving the minor class the "opportunity" to be preserved in the image context. This strategy is shown to be:

1. Consistent with each minor class;
2. Consistent with each image-object;
3. Consistent with the entire image context; and
4. Suitable for automatic and unsupervised processing.
For each image-object the process selects the most appropriate area to *re-introduce* those *minor classes* which are considered quantitatively important (relating to the particular image-object). The strategy is:

1. Consistent allowing the information to be emphasised where it is originally most predominant;
2. Essential control to guarantee cartographic quality to the final representation of simplified information;
3. Suitable for objective simulation of the cartographer’s activity of emphasising information in an automatic and unsupervised process; and
4. Objective and generally applicable and consistent with the original information.

### 6.8 Input for the Semantic Generalization

The product of main polygons obtained by the rule-based merging of image-objects is the input for the Semantic Generalization described in the following chapter. The unclassified pixels forming the black regions occurring in the output illustrated in the previous section are not suitable for an automatic processing of the polygons in the image. The product $A$ obtained by the merging guided by the second rule $TP\_Merging\_Rule$ has produced black regions in areas covering one single theme where, in case of optimal conditions (i.e. if those areas would have been “visible” to the process) the smoothing performance was expected to be correct, while the product $B$ obtained by the third rule $TG\_Merging\_Rule$ has produced a more complex distribution of black regions covering thematically mixed areas, for which the provisions on how the smoothing would have worked were unpredictable. For this reason, the product of the second rule $TP\_Merging\_Rule$ containing 223 main polygons has been chosen for manual correction which, however, has limited to the minimum the introduction of uncertain information with no repercussions for the performance of the consequent Semantic Generalization. The input data for the Semantic Generalization is illustrated in Fig. 6.23.
Fig. 6.23. Input for the Semantic Generalization obtained by the manipulations on the image of 223 main polygons produced by the Geometrical Generalization (Fig. 6.21).
Comparing products in Fig. 6.21 and Fig. 6.23, one may notice that black regions are concentrated in large and homogeneous polygons, associated to: "horticulture", "grassland", "soil" and "urban", which are main themes in the original classified image. The black regions in the product shown in Fig. 6.22 involves also minor classes, for which the erroneous introduction or reduction of pixels (during the manual correction) may compromise the original balancing of image-classes. The choice of correcting the product shown in Fig. 6.21 as becoming the input for the Semantic generalization has reduced the propagation of error, evaluated as minimum in section 8.13, which has not however compromised the individual and global performance of the Generalization processes, as fully discussed in chapter 8.
CHAPTER 7 SEMANTIC GENERALIZATION

7.1 Introduction to the Semantic Generalization

7.2 Rule-Based Image-Class Conversion System

7.2.1 Automatic Image-class Re-Labelling Process

7.2.2 The Hypotheses Verification Process

7.2.2.1 Hypotheses Verification for Image-class Urban

7.2.2.2 Hypotheses Verification Process for Image-class Soil

7.3 Presentation of the Final Generalized Product

7.4 Results Obtained by the Semantic Generalization Process

7.5 Summary of the Semantic Generalization
CHAPTER 7
SEMANTIC GENERALIZATION

7.1 Introduction to the Semantic Generalization

The main tasks for the Semantic Generalization process are: 1) conversion of the geometrically generalized product from the low level land cover nomenclature to the high level CORINE land use nomenclature, and 2) formatting the final product to be compatible with a GIS. These two activities are performed either on the entire low level generalized image or polygon-by-polygon. The Semantic Generalization process consists of a Rule-Based System which applies different sets of rules at different stages of its reasoning to the product of the geometrical generalization.

During the image-class conversion individual rules or group of rules are specifically applied to specific image-classes, which allows a finer class-to-class or classes-to-class conversion. At each stage image-classes satisfying the rules are directly re-labelled and are not involved in the subsequent reasoning.

The re-organisation of the CORINE nomenclature was necessary in order to design an objective scheme of conversion rules suitable for automatic processing. As introduced in section 2.3 and explained in chapter 3 the CORINE land use classes (see Table 2.2) have been defined for manual-visual interpretation, from which it follows that several classes are not distinguished by automatic interpretation, for example the CORINE class Green Urban Areas (1.4.1) cannot be distinguished from the class Sport and Leisure Facilities (1.4.2). For this reason it was necessary to re-arrange the CORINE nomenclature in order to collate all CORINE land use classes automatically comparable with a spectral classification scheme.

The Pseudo CORINE Classes (Pcor) nomenclature was then organised to contain all CORINE classes automatically detectable and the parent of each CORINE class which is not automatically recognisable from satellite images, as illustrated in Table 7.1. Parents are one of the 5 CORINE grouping class in the second level of the land use hierarchy of classes as shown in Table 2.2. The parent of classes not easily recognisable from satellite images has been chosen as being: 1) a CORINE class and 2) clearly associate to spectral classes. CORINE classes which presents spectral characteristics similar to other CORINE classes (in the same bottom level) are grouped under one single Pseudo CORINE class in Pcor. For example,
although the CORINE classes 2.3.1 Pastures and 3.2.1 Natural grassland have different parents in the CORINE land use hierarchy (see Table 2.2) they are spectrally similar and both of them have been associated with a unique CORINE label which is the 3.2.1 Natural grassland.

The CORINE classes 1.3.1 Mineral extraction sites, 1.3.2. Dump sites and 1.3.3. Construction sites have been associated with their common parent 1.3 Mine, dump and construction sites, since they are not expected to be spectrally different. It is also difficult to imagine that these classes can be spectrally detectable, however they must be maintained in the land use nomenclature as being essential information to be reported in a map when considering the real scenario. More sophisticated rules using information in the form of digital maps, when available, may be designed in a second stage of processing.

The CORINE classes 1.4.1 Green urban areas and 1.4.2 Sport and Leisure facilities have been associated with their common parent class 1.4 Artificial, non-agricultural vegetated areas. These classes are a combination of the CORINE classes 3.2.1 Natural grassland and 1.1.1 Continuous urban fabric and are expected to be recognised by shape detection algorithms. The large amount of literature about shape detection, the common practice of combining different satellite-data with different spatial resolution, of using digital maps or other digital information, and the practice of organising sophisticated rule-based systems support the expectation of realising such an automatic rule-based procedure. Thus grassland areas characterised by regular shape, circular or rectangular and separated from other grassland areas by footpaths or by small roads are expected to be effectively recognised. With similar reasoning sport facilities are expected to be recognised by detection of the shape of elliptical running paths, by measuring the regular distribution of rectangular warehouses and/or by recognising outdoor swimming pools (rectangular or circular water objects in a continuous urban area).

The classes 1.2.1 Industrial or commercial units and 1.2.2 Road and rail networks and associated land have been associated with their common parent 1.2 Industrial, commercial and transport units. With a more complex hierarchical rules scheme, also integrating different spatial information, rail and road networks connecting industrial areas in the same region are expected to be automatically detected. "Airports and Ports areas" are also included in the definition of "automatically recognisable" classes as detectable by the combination of shape
and context techniques and integrating different sources of data, they are also included in the
group class 12 Industrial, commercial, transport units.

The classes 2.2.2 Fruit trees and berry plantation and 2.2.3 Olive groves cannot be
individually derived from the simple 10 classes classified image used in this work. Therefore
these CORINE classes have been associated with the class 2.4.4 Agro-forestry areas.

The Semantic Generalization elaborates the final layout of the generalized product by
performing a spatial generalization in two steps which produces two raster thematic products
respectively constrained to different minimum mapping units, 10 hectares and 25 hectares.
<table>
<thead>
<tr>
<th>CORINE land use classes</th>
<th>Pseudo CORINE land use classes</th>
</tr>
</thead>
<tbody>
<tr>
<td>111</td>
<td>111 continuous urban fabric</td>
</tr>
<tr>
<td>112</td>
<td>112 discontinuous urban fabric</td>
</tr>
<tr>
<td>121</td>
<td>12 industrial, commercial transport units</td>
</tr>
<tr>
<td>122</td>
<td>&quot;</td>
</tr>
<tr>
<td>123</td>
<td>&quot;</td>
</tr>
<tr>
<td>124</td>
<td>&quot;</td>
</tr>
<tr>
<td>131</td>
<td>13 construction sites</td>
</tr>
<tr>
<td>132</td>
<td>&quot;</td>
</tr>
<tr>
<td>133</td>
<td>&quot;</td>
</tr>
<tr>
<td>141</td>
<td>14 artificial, non-agricultural vegetated areas</td>
</tr>
<tr>
<td>142</td>
<td>&quot;</td>
</tr>
<tr>
<td>211</td>
<td>211 non-irrigated arable land</td>
</tr>
<tr>
<td>212</td>
<td>21 rice fields (aquatic vegetation)</td>
</tr>
<tr>
<td>213</td>
<td>&quot;</td>
</tr>
<tr>
<td>221</td>
<td>221 vineyards</td>
</tr>
<tr>
<td>222</td>
<td>244 agro-forestry</td>
</tr>
<tr>
<td>223</td>
<td>&quot;</td>
</tr>
<tr>
<td>231</td>
<td>321 natural grassland</td>
</tr>
<tr>
<td>241</td>
<td>24 heterogeneous agricultural areas</td>
</tr>
<tr>
<td>242</td>
<td>&quot;</td>
</tr>
<tr>
<td>243</td>
<td>&quot;</td>
</tr>
<tr>
<td>244</td>
<td>244 agro-forestry</td>
</tr>
<tr>
<td>311</td>
<td>31 forests</td>
</tr>
<tr>
<td>312</td>
<td>&quot;</td>
</tr>
<tr>
<td>313</td>
<td>&quot;</td>
</tr>
<tr>
<td>321</td>
<td>321 natural grassland</td>
</tr>
<tr>
<td>322</td>
<td>32 scrub, herbaceous vegetation</td>
</tr>
<tr>
<td>323</td>
<td>&quot;</td>
</tr>
<tr>
<td>324</td>
<td>&quot;</td>
</tr>
<tr>
<td>331</td>
<td>331 beaches, dunes, sands</td>
</tr>
<tr>
<td>332</td>
<td>33 open spaces with little or no vegetation</td>
</tr>
<tr>
<td>333</td>
<td>&quot;</td>
</tr>
<tr>
<td>334</td>
<td>&quot;</td>
</tr>
<tr>
<td>335</td>
<td>335 glaciers and perpetual snow</td>
</tr>
<tr>
<td>411</td>
<td>41 inland wetlands</td>
</tr>
<tr>
<td>412</td>
<td>&quot;</td>
</tr>
<tr>
<td>421</td>
<td>42 maritime wetlands</td>
</tr>
<tr>
<td>422</td>
<td>&quot;</td>
</tr>
<tr>
<td>423</td>
<td>422 salines</td>
</tr>
<tr>
<td>511</td>
<td>51 inland water bodies</td>
</tr>
<tr>
<td>512</td>
<td>&quot;</td>
</tr>
<tr>
<td>521</td>
<td>52 seas, oceans</td>
</tr>
<tr>
<td>522</td>
<td>&quot;</td>
</tr>
<tr>
<td>523</td>
<td>&quot;</td>
</tr>
</tbody>
</table>

Table 7.1. The Pseudo CORINE land use nomenclature used by the Semantic Generalization to convert the land cover classes occurring in the Geometrically Generalized product. See Table 3.2.1 for direct comparison with the CORINE land use nomenclature.
7.2 Rule-Based Image-Class Conversion System

By the analysis of the CORINE land use nomenclature and typical spectral land cover classification schemes, one notes the occurrence of category names which are directly related to single image-classes. For example, the commonly used image-class "cereal" (or "cereals") may be directly associated with the CORINE class 211 "non-irrigated arable land". This consideration led to the organisation of the image-class conversion process in two main steps, described in following sections:
1. Automatic Image-class Re-labelling Process; and

7.2.1 Automatic Image-class Re-Labelling Process

Dictionaries of synonyms have been organised and used at this stage of the conversion of image-classes for fast and automatic translation of those image-classes for which a one-to-one relationship exist with single CORINE land use classes. An automatic strategy for syntactic comparison is used to objectively, and quickly, solve the problem of two class belonging to both schemes but with different names. For this purpose, a dictionary of synonyms for each class belonging to the two classification schemes has been organised. This kind of dictionary is easy to maintain and update, and a universal dictionary of synonyms may be created satisfying the majority of land cover spectral classification systems.

The Spectral Classes Dictionary (SCDictionary) of the low level classes and the Pseudo Corine Classes Dictionary (PcorDictionary) of the Pcor classes are shown in Table 7.2 and Table 7.3. The syntax procedure for the automatic re-labelling works on one low level class at a time, and all the synonyms in the SCDictionary are compared to each synonym associated with each Pcor class in the PcorDictionary. When a match is found, the syntax search stops, and the low level class is re-labelled as the Pcor owner of the matching synonym.
### SPECTRAL CLASSES DICTIONARY

<table>
<thead>
<tr>
<th>CLASS NAME</th>
<th>SYNONYMS</th>
</tr>
</thead>
<tbody>
<tr>
<td>1 soil</td>
<td>soil, ground</td>
</tr>
<tr>
<td>2 grass</td>
<td>grass, grassland, natural grassland</td>
</tr>
<tr>
<td>3 water</td>
<td>water, water courses, water bodies</td>
</tr>
<tr>
<td>4 cereals</td>
<td>cereal, cereals, cereals cultivation, non-irrigated cultivation</td>
</tr>
<tr>
<td>5 forest</td>
<td>forest, forests</td>
</tr>
<tr>
<td>6 urban</td>
<td>urban areas</td>
</tr>
<tr>
<td>7 vineyard</td>
<td>vineyard, vineyards, vineyards cultivation</td>
</tr>
<tr>
<td>8 horticulture</td>
<td>mixed crops, non-homogeneous crops, heterogeneous cultivation, mixed irrigated crops</td>
</tr>
<tr>
<td>9 aquatic vegetation</td>
<td>rice cultivation, rice fields, rice, aquatic cultivation, aquatic vegetation</td>
</tr>
<tr>
<td>10 marshes</td>
<td>marshes, wetland, wetlands</td>
</tr>
</tbody>
</table>

Table 7.2. SCDictionary used by the Automatic Relabelling process of the Semantic Generalization.

### PSEUDO CORINE CLASSES DICTIONARY

<table>
<thead>
<tr>
<th>CLASS NAME</th>
<th>SYNONYMS</th>
</tr>
</thead>
<tbody>
<tr>
<td>211 non-irrigated arable land</td>
<td>non-irrigated arable land, non-irrigated arable crops, cereals, legumes, fodder crops, industrial plants, root crops, fallow land, arable land</td>
</tr>
<tr>
<td>213 rice fields</td>
<td>rice, rice fields, rice cultivation, aquatic vegetation</td>
</tr>
<tr>
<td>221 vineyards</td>
<td>vineyard, vineyards, vine cultivation, vineyard cultivation</td>
</tr>
<tr>
<td>24 heterogeneous agricultural land</td>
<td>irrigated agricultural land, heterogeneous crops, mixed crops</td>
</tr>
<tr>
<td>244 agro-forestry</td>
<td>agro-forestry, agriculture and forest areas, annual crops and forest</td>
</tr>
<tr>
<td>321 natural grassland</td>
<td>grassland, grass, natural grass</td>
</tr>
<tr>
<td>411 inland wetlands</td>
<td>marshes, peat bogs, flooded lands, wetlands</td>
</tr>
<tr>
<td>51 inland waters</td>
<td>water, inland water, water bodies, water courses, lake</td>
</tr>
</tbody>
</table>

Table 7.3. Example of the PcorDictionary used by the Automatic Relabelling process of the Semantic Generalization.
7.2.2 The Hypotheses Verification Process

At this stage of image-class conversion all low level classes, for which no direct one-to-one relationship with a single Pcor land use class exists, are individually examined in their thematic context and consequently converted.

The expert system implemented for the conversion of low level classes (image-classes) into Pcor classes by using only the spectral information derived from the input classified image maintains the principal of automatically and dynamically extracting the necessary knowledge from the low level generalized image. The approach used for the inference mechanism consists of iterative per-class contextual reasoning which evaluates hypotheses in order to identify the thematic context associated with each thematic area in the low level generalized image. Once the thematic context is identified, the process performs the most appropriate class-to-class conversion. When the thematic context of a low level area is not "clearly" identifiable, the low level area is not converted, based on the principle that a "correct" low level class in the final map is better than an uncertain Pcor land use class. Models representing the ideal thematic context of Pcor land use classes for low level class in the classification scheme are pre-defined to support the per-area reasoning of the expert system. Each model has an associated set of hierarchical thematic and logical hypotheses which are automatically verified by the process while analysing any thematic area in the image.

A similar strategy has also been used by Kartikeyan et al. (1995), presenting an expert system for per-pixel land cover classification based on a mechanism of inferring the land cover types according to hypotheses-based evidential reasoning. Despite the different application, the strategy used for the verification of a hierarchical group of hypothesis has been demonstrated in this thesis to be appropriate also for the generalization problem, where both the natural hierarchical relationship among land cover classes and the hierarchical relationship between land cover classes and land use types must be respected.

The hypothesis verification process developed for this thesis analyses each low level area in the context of the polygon in which the low level area is found; allowing a semantic generalization consistent with the input spatial data. In fact, once the geometrically generalized image from the spectral land cover classification scheme is converted to the Pcor land use nomenclature, the final product is still representative of the input spatial
characteristics, while being directly comparable with digital CORINE data. Hypotheses are mutually exclusive avoiding (on the contrary to Kartikeyan) the re-calculation (or the tracking) of all the activated rules from the top to the bottom level of the hierarchy before the effective class-to-class conversion takes place.

In the case of the implemented version of the expert system, two thematic models have been designed corresponding to the two image-classes still to be converted after the application of the Automatic Relabelling Process. These classes are: 1) urban and 2) soil. Further the structure of the expert system has been prepared for extension by the addition of other models.

Two separate sets of hypotheses (explained in sections 7.2.2.1 and 7.2.2.2) have been formulated to represent the models associated with the image-classes urban and soil in order to identify the type of thematic context which surrounds areas of these image-classes. The thematic context may be either internal to the polygon which the area under analysis belongs to or be external to it, i.e. associated with the adjacents of the polygon which the low level area under analysis belongs to. Hypotheses are "verified" by production rules (section 2.5.2) which are activated by the verification processes; the verification of an hypothesis determines the activation of the consequent action associated with the rule which verified the hypothesis. The same set of hypotheses are applied to process each area in the image labelled with the same low level class, but the activation of a specific rule depends on the thematic context surrounding that particular area. By accessing the text files edge_poly.dat, polygon_class.dat and adjs_file.dat, the process organises the information necessary for the contextual reasoning, in two new text files: classes_freq.dat which contains for each polygon the list of frequencies, in number of pixels, of each image-class in the polygon, and area_perc_l_4.dat, which contains for each polygon the value corresponding to 25% of the area internal to the polygon, which is used as a logical constraint during the contextual reasoning. One image-class is examined at a time and all the areas associated with that class are independently analysed until they are converted into a Pcor class. The image is directly modified whenever a class-to-class relationship is found by the process. The process is iterative and stops when no more class-to-class conversions are performed, i.e. when the thematic context in the image is such that no more hypotheses are verified.
7.2.2.1 Hypotheses Verification for Image-class Urban

The hypothesis supporting this process is that any "urban" area in the classified image surrounded by natural or agricultural areas may be logically considered as a minor urban agglomeration, for example a village in the countryside, therefore it may be associated with the Pcor class (112) "Discontinuous urban fabric". Any "urban" area in the classified image surrounded by areas associated with Pcor classes such as "continuous urban fabric" or "industrial or commercial" may be logically considered as a major urban agglomeration, such as a city and may therefore be associated with the Pcor class (111) "Continuous urban fabric". The two sets of Pcor classes have been defined for this purpose:

\[ Set_1 = \{112, 21, 211, 221, 24, 244, 30, 33\} \]
\[ Set_2 = \{111, 12\} \]

The Pcor classes chosen to form the two sets are considered both necessary and sufficient to provide an objective discrimination between a "city" and a "village". For each polygon containing an area associated with the image-class "urban", the internal population is examined in order to calculate the existence of Pcor classes belonging respectively to \( Set_1 \) or \( Set_2 \). For example, given \( tot_{pcor_1} \) and \( tot_{pcor_2} \) (respectively the number of Pcor classes belonging to \( Set_1 \) and \( Set_2 \) occurring in the polygon) four hypotheses are proposed at this stage of processing, each of which is associated with one production rule. The verification of one hypothesis determines the activation of the corresponding rule and the associated consequent actions. Hypotheses and rules for the contextual reasoning specific for the land cover class "urban" are described below:

\[ Hypotheses_1: \quad tot_{pcor_1} >= 1 \text{ AND } tot_{pcor_2} = 0 \]
\[ Hypotheses_2: \quad tot_{pcor_1} = 0 \text{ AND } tot_{pcor_2} >= 1 \]
\[ Hypotheses_3: \quad tot_{pcor_1} >= 1 \text{ AND } tot_{pcor_2} >= 1 \]
\[ Hypotheses_4: \quad tot_{pcor_1} = 0 \text{ AND } tot_{pcor_2} = 0 \]
Urban Rule 1: IF Hypotheses 1 is TRUE
            THEN call Routine F3(sc_to_relabel, pcor)

Urban Rule 2: IF Hypotheses 2 is TRUE
            THEN call Routine F3(sc_to_relabel, pcor)

Urban Rule 3: IF Hypotheses 3 is TRUE
            THEN call Routine F4(sc_to_relabel)

Urban Rule 4: IF Hypotheses 4 is TRUE
            THEN call Routine F4(sc_to_relabel)

Routine Name: F3(sc_to_relabel, pcor)
Description: performs a direct substitution of the image-class sc_to_relabel with the
Pcor class pcor. In the particular case of Urban Rule 1 and Urban Rule 2, sc_to_relabel is
image-class “urban” and pcor is respectively Pcor class 112 and Pcor class 111

Routine Name: F4(sc_to_relabel)
Description: performs a second stage contextual reasoning involving the adjacent
neighbourhood of the polygon in which the “urban” area under analysis was detected.
Depending on the image-class sc_to_relabel the appropriate reasoning process is activated. In
the particular case in which sc_to_relabel is “urban” the Routine F6() is called

Routine Name: F6()
Description: calculates the values tot_pcor1 and tot_pcor_2 corresponding to the
adjacent neighbourhood and the four hypotheses previously described are newly proposed by
the opportune rules as described below:
Semantic Generalization

**Urban_Rule_5:** IF Hypotheses_1 is TRUE
THEN call Routine $F3(sc_{-}to_{-}relabel, pcor)$ $(pcor = 112)$

**Urban_Rule_6:** IF Hypotheses_2 is TRUE
THEN call Routine $F3(sc_{-}to_{-}relabel, pcor)$ $(pcor = 111)$

**Urban_Rule_7:** IF Hypotheses_3 is TRUE
THEN no conversion is performed for the area under analysis in this iteration

**Urban_Rule_8:** IF Hypotheses_4 is TRUE
THEN no conversion is performed for the area under analysis in this iteration

The last rule **Urban_Rule_8** means that without sufficient information no class-to-class allocation is made. The idea is that when there is no certainty it is better to leave the low level area as it is rather than introducing an inappropriate conversion. The image context is dynamically updated during the contextual reasoning at each class-to-class conversion, and the process is iterative until no more low level areas occur in the image or until the spatial and thematic conditions do not allow any class-to-class allocation. Therefore any "urban" area which is not converted in the current iteration, will be examined (in a new context) in the consequent iteration until converted. When ambiguous information occur in the vicinity surrounding the "urban" area under analysis, that area will not be converted to any Pcor class because of the absence of objective evidence.
7.2.2.2 Hypotheses Verification Process for Image-class Soil

Image-class soil is the most ambiguous low level category in the input classification scheme as it may be equally associated with many Pcor classes. For example, a “soil” area in the classified image of Portugal derived from a satellite image sensed in the month of June may represent in reality an unused dry field of crops, a dry field of grass, bare soil, sand an unused dry rice field, a dry marsh land or an unused construction site. A “soil” area in a classified image could be anything in reality, as the available information is only derived from the classified image is not sufficient.

The contextual reasoning for the consistent conversion of low level “soil” areas into Pcor categories analyses the population statistics associated with the polygon in which the “soil” area has been detected together with the adjacent neighbourhood of the polygon in order to identify the type of thematic context in which the “soil” area occurs. The logic of the contextual reasoning establishing the existence of necessary and sufficient conditions for the conversion of “soil” areas are:

1. The “soil” area must predominate within the polygon; and
2. A “compatible” Pcor class must also exist in the polygon.

Otherwise, more detailed controls on a “larger” neighbourhood are necessary to identify an appropriate class-to-class relationship.

The identification of the thematic context associated with each “soil” area in the low level generalized product is concerned with the identification of the:

- **Quantitative importance** of the “soil” area within the polygon;
- **Quantitative importance** of any other category (low level or Pcor) in the same polygon where the “soil” area is found;
- **Quantitative importance** of any other category (low level or Pcor) in the neighbourhood of the polygon in which the “soil” area is found; and
- **Thematic compatibility** between the image-class soil and Pcor classes, i.e. the selection of those Pcor classes for which a conversion of a “soil” area is reliable.

In the context of the semantic generalization presented in this thesis, to be “quantitatively important” within a polygon, a certain category (low level or Pcor) must represent at least 25% of the entire polygon’s area. This logical threshold is not variable and is considered a sufficient condition for objective evaluations considering the relatively “small”
extension of the thematic patches generally occurring in a classified (or post-classified) image. This information concerning each polygon is collected in the text file `area_perc_1_4.dat`.

The image-class *soil*, as pointed out at the start of this section, may in reality be spectrally associated with several land use types. For the expert system, this represents the *relationship of compatibility* between the image-class *soil* and specific Pcor classes, shown in Table 7.4, and within which the process selects the most convenient category for the conversion of each “soil” area. The relationship of compatibility has been defined collecting all those Pcor classes which may present “mixed” spectral characteristics including those similar to the class “soil”.

<table>
<thead>
<tr>
<th>Relationship of Compatibility between the land cover class <em>Soil</em> and Pcor classes</th>
</tr>
</thead>
<tbody>
<tr>
<td>111 Continuous Urban Fabric</td>
</tr>
<tr>
<td>112 Discontinuous Urban Fabric</td>
</tr>
<tr>
<td>12 Industrial, Commercial, Transport Units</td>
</tr>
<tr>
<td>13 Construction Sites</td>
</tr>
<tr>
<td>211 Non-irrigated Arable Land</td>
</tr>
<tr>
<td>24 Heterogeneous Agricultural Areas</td>
</tr>
<tr>
<td>244 Agro-Forestry</td>
</tr>
<tr>
<td>32 Scrub, Herbaceous vegetation</td>
</tr>
<tr>
<td>321 Natural Grass</td>
</tr>
<tr>
<td>33 Open Spaces with Little or No Vegetation</td>
</tr>
<tr>
<td>331 Beaches, Dunes, Sand</td>
</tr>
</tbody>
</table>

Table 7.4. Set of Pcor classes used by the conversion process of the Semantic Generalization to select the most appropriate Pcor class to convert a low level “soil” area.

A *6-levels hierarchy of hypotheses* has been organised for this research to support the contextual reasoning for the image-class *soil*: the structure of which is shown in Fig. 7.1. There are three main hypotheses, A, B and C, from which three separate hierarchical branches of hypotheses depart. Hypotheses are applied to each polygon within which the image-class *soil* is detected. When the contextual reasoning arrives at the bottom of the hierarchy to nodes labelled as S and T, it means that the thematic context of the “soil” area under analysis has been identified and that an appropriate class-to-class relationship has been selected. When the contextual reasoning arrives at a node labelled as R, it means that the analysis of the internal
population is not sufficient to identify the thematic context of the “soil” area under analysis and therefore the analysis of the adjacent neighbourhood is required.

The description of all hypotheses in the scheme and associated rules is given below:

**Hypotheses A:** the low level class *soil* is the majority class within the polygon

- **D:** there aren’t Pcor classes within the polygon
- **E:** there are Pcor classes within the polygon
  - **L:** there are quantitatively important Pcor classes within the polygon
  - **R:** there aren’t compatible Pcor classes within the polygon
  - **S:** there is only one compatible Pcor class within the polygon
  - **T:** there are several compatible Pcor classes within the polygon
- **M:** there aren’t quantitatively important Pcor classes within the polygon

**Hypotheses B:** the low level class *soil* is the minority class within the polygon

- **F:** the low level class *soil* is not quantitative important within the polygon
  - **L:** there are quantitatively important classes within the polygon
  - **R:** there aren’t compatible Pcor classes within the polygon
  - **S:** there is only one compatible Pcor class within the polygon
  - **T:** there are several compatible Pcor classes within the polygon
- **M:** there aren’t quantitatively important classes within the polygon

**G:** the low level class *soil* is quantitatively important within the polygon

- **N:** there is only one Pcor class within the polygon
  - **U:** this Pcor class is quantitatively important within the polygon
  - **R:** this Pcor class is not compatible
  - **S:** this Pcor class is compatible
  - **V:** this Pcor class is not quantitatively important within the polygon
- **O:** there are several Pcor classes within the polygon
  - **W:** the major of the Pcor classes within the polygon is statistically important and compatible
**X:** the major of the Pcor classes within the polygon is statistically important but not compatible

**Z:** there are minor Pcor classes which are statistically important within the polygon

**R:** there aren’t compatible Pcor classes within the polygon

**S:** there is only one compatible Pcor class within the polygon

**T:** there are several compatible Pcor classes within the polygon

**Y:** there aren’t minor Pcor classes which are statistically important within the polygon
Fig. 7.1. The 6-levels Hierarchy of Hypotheses supporting the contextual reasoning for the conversion of the low level class *Soil.*
**Hypotheses**

**C:** the low level class *soil* is neither the majority class nor the minority class within the polygon

**H:** the low level class *soil* is not quantitatively important within the polygon

**P:** there are quantitatively important Pcor classes within the polygon

**R:** there aren't compatible Pcor classes within the polygon

**S:** there is only one compatible Pcor class within the polygon

**T:** there are several compatible Pcor classes within the polygon

**Q:** there aren't quantitatively important Pcor classes within the polygon

**I:** the low level class *soil* is quantitatively important within the polygon

**J:** the majority class within the polygon is quantitatively important and is a compatible Pcor class

**K:** the majority class within the polygon is quantitatively important but is not a compatible Pcor class

**Z:** there are minor Pcor classes which are quantitatively important within the polygon

**R:** there aren't compatible Pcor classes within the polygon

**S:** there is only one compatible Pcor class within the polygon

**T:** there are several compatible Pcor classes within the polygon

**Y:** there aren't minor Pcor classes which are quantitatively important within the polygon
Rules associated with the Hypotheses Verification Process for the low level class *Soil* are listed below:

**Soil_Rule_Main:**

\[
\begin{align*}
&\text{IF } Hypotheses_\text{A} \text{ is TRUE} \\
&\quad \text{THEN call Soil_Rule_1} \\
&\quad \text{ELSE IF } Hypotheses_\text{B} \text{ is TRUE} \\
&\quad\quad \text{THEN call Soil_Rule_2} \\
&\quad\quad \text{ELSE IF } Hypotheses_\text{B} \text{ is TRUE} \\
&\quad\quad\quad \text{THEN call Soil_Rule_3} \\
&\quad \text{END}
\end{align*}
\]

**Soil_Rule_1:**

\[
\begin{align*}
&\text{IF } Hypotheses_\text{E} \text{ is TRUE} \\
&\quad \text{THEN call Routine } F1() \\
&\quad\quad \text{call Soil_Rule_4} \\
&\quad \text{ELSE IF } Hypotheses_\text{D} \text{ is TRUE} \\
&\quad\quad \text{THEN call Routine } F4() \\
&\quad \text{END}
\end{align*}
\]

**Soil_Rule_4:**

\[
\begin{align*}
&\text{IF } Hypotheses_\text{L} \text{ is TRUE} \\
&\quad \text{THEN call Routine } F2() \\
&\quad\quad \text{call Soil_Rule_5} \\
&\quad \text{ELSE IF } Hypotheses_\text{M} \text{ is TRUE} \\
&\quad\quad \text{THEN call Routine } F4() \\
&\quad \text{END}
\end{align*}
\]
Soil_Rule_5: IF Hypotheses_R is TRUE
THEN call Routine F4()
ELSE IF Hypotheses_S is TRUE
THEN call Routine F3()
ELSE IF Hypotheses_T is TRUE
THEN choose the major among the compatible Pcor classes within in the polygon and call Routine F3()
END

Soil_Rule_2: IF Hypotheses_F is TRUE
THEN call Routine F1()
call Soil_Rule_6
ELSE IF Hypotheses_G is TRUE
THEN call Soil_Rule_7
END

Soil_Rule_6: IF Hypotheses_L is TRUE
THEN call Routine F2()
call Soil_Rule_5
ELSE IF Hypotheses_M is TRUE
THEN call Routine F4()
END
Soil_Rule_7: IF Hypotheses_N is TRUE
    THEN call Routine F1()
    call Soil_Rule_8
ELSE IF Hypotheses_O is TRUE
    THEN call Routine F1()
    call Routine F2()
    call Soil_Rule_9()
END

Soil_Rule_8: IF Hypotheses_U is TRUE
    THEN call Routine F2()
    call Soil_Rule_5
ELSE IF Hypotheses_V is TRUE
    THEN call Routine F4()
END

Soil_Rule_9: IF Hypotheses_W is TRUE
    THEN call Routine F3()
ELSE IF Hypotheses_X is TRUE
    THEN call Soil_Rule_10
END

Soil_Rule_10: IF Hypotheses_Z is TRUE
    THEN call Soil_Rule_5
ELSE IF Hypotheses_Y is TRUE
    THEN call Routine F4()
END
Soil_Rule_3: IF Hypotheses_H is TRUE
         THEN call Routine F1()
         call Soil_Rule_11
         ELSE IF Hypotheses_I is TRUE
         THEN call Routine F1()
         call Routine F2()
         call Soil_Rule_12
         END

Soil_Rule_11: IF Hypotheses_P is TRUE
              THEN call Routine F2()
              call Soil_Rule_5
              ELSE IF Hypotheses_Q is TRUE
              THEN call Routine F4()
              END

Soil_Rule_12: IF Hypotheses_J is TRUE
              THEN call Routine F3()
              ELSE IF Hypotheses_K is TRUE
              THEN call Soil_Rule_13
              END

Soil_Rule_13: IF Hypotheses_Z is TRUE
              THEN call Soil_Rule_5
              ELSE IF Hypotheses_Y is TRUE
              THEN call Routine F4()
              END
Routine Name: $F1()$
Description: evaluates the *quantitative importance* of all the classes (low level and Pcor) within the polygon currently being analysed.

Routine Name: $F2()$
Description: evaluates the occurrence of Pcor classes *compatible* with the low level class *soil* among the quantitatively important classes within the polygon.

Routine Name: $F3(sc_to_relabel, pcor)$
Description: performs a direct substitution of the image-class *sc_to_relabel* with the Pcor class *pcor*. In the particular case of the contextual reasoning for the image-class *soil* *sc_to_relabel* is image-class “soil” and *pcor* depends on the verified hypotheses for which the routine has been called.

Routine Name: $F4(sc_to_relabel)$
Description: performs a second stage contextual reasoning involving the adjacents of the polygon to which the “soil” area under analysis belongs. Depending on the image-class *sc_to_relabel* the appropriate reasoning process is activated. In this particular case *sc_to_relabel* is “soil” and the Routine $F5()$ is called.

Routine Name: $F5(sc_to_relabel)$
Description: checks the population of the adjacent neighbourhood of the polygon within which the “soil” area was detected, by calling the Routines $F1()$ and $F2()$. In the case of the occurrence in the adjacents of Pcor classes which are *quantitatively important* and *compatible* with the image-class *soil* the majority class within the entire adjacent neighbourhood is chosen for converting the “soil” area, calling the Routine $F3()$. In the case that none of the occurring classes in the adjacent neighbourhood are compatible with the image-class *soil* no conversion is performed because of the presence of ambiguous information. For the this reason, as commented above for *Urban_Rule_8*, some of the “soil” areas might not be converted at the end of the processing.
7.3 Presentation of the Final Generalized Product

The final stage of the Generalization Activity is the presentation of the generalized information in a format suitable for direct input to a GIS. The generalized product presents, after the execution of the expert system, thematic patches which are “large” and homogeneous when compared with other classified images, but “small” and heterogeneous when compared with digital cartographic maps.

The task for the final stage of the generalization process is to perform a further spatial generalization in order to create a more homogeneous product satisfying the spatial characteristics required for direct comparison with GIS land use maps. Two spatial constraints have been tested in this final process: a minimum mapping unit (MMU) of 25 hectares, as required by the CORINE maps, and a minimum mapping unit of 10 hectares, as mentioned in section 3.2 and considered a suitable compromise between the size of the mapped areas and the detail of the land use nomenclature. In section 3.2 the contradictory use in CORINE maps of a finely detailed land use nomenclature for very extended areas measuring at least 25 hectares was mentioned.

The two spatial constraints (thresholds) are calculated in terms of pixels as follows:

- 1 hectare is 10,000 metres squared is approximately 11 pixels
- 10 hectares is 100,000 metres squared is approximately 111 pixels
- 25 hectares is 250,000 metres squared is approximately 278 pixels

The spatial generalization is performed as described below:

\[\text{Verification\_on\_MinAreaSize(threshold)}\]

FOR each polygon{

- the majority \textit{Pcor class} is determined
- the \textit{threshold} on the majority class is \textit{evaluated}

IF the \textit{majority class} satisfies the \textit{threshold}

THEN all the classes occurring within the polygon are substituted by the \textit{majority class}
ELSE the adjacent neighbourhood of the polygon is examined, analysing all
adjacents of the polygon and calculating a *global majority Pcor
class*. which is then assigned to the whole polygon's area

END

Technically the merging process is performed per-object, anonymously and until no
changes occur in the raster image. No priority order is given to the Pcor class during the
merging. In this way at each iteration all the polygons satisfying the MMU in the raster image
are anonymous candidates for merging. The modification of the merging algorithm with the
constraint that only one Pcor category is analysed at a time until no more changes occur in the
areas of the current Pcor category might be fruitful approach for future research.

7.4 Results Obtained by the Semantic Generalization Process

In this section the results obtained by the Semantic Generalization process on the
geometrically generalized product, shown in Fig. 6.23, are presented. The first processing step
of the *Expert System* described in section 7.2.1, is the *Automatic Re-Labelling Process* which
produces the image shown in Fig. 7.2. Eight land cover classes have been automatically
converted into Pcor classes as they were directly and logically connected to corresponding
Pcor classes by a single class-to-class relationship, easily and successfully executed by a
"syntax match". Only the land cover classes "urban" and "soil" have not been converted at
this stage of processing as they present a "one-to-many" relationship with Pcor classes, as
explained in section 7.2.2.

"Urban" and "soil" land cover areas have been analysed by the second processing step
of the expert system, the *Rule-based Contextual Reasoning Process*, as described in section
7.2.2. land cover "Urban" and "soil" areas have been automatically converted consistently to
their specific spatial and thematic surrounding context, as may be observed from the resulting
product shown in Fig. 7.3 which represents the final product generated by the expert system.
In this image some polygons contain horizontal lines associated with the land cover class
«soil». This error is related to the procedures responsible for determining the internal region
of a polygon (*FindIntExtPolygon()* as explained in section 5.3.
The third processing step of the semantic generalization is the *Presentation of the Final Generalized Product* in a format suitable to be directly compared with GIS digital CORINE land use maps, as explained in section 7.3. The two derived products are shown in Figures 7.4 and 7.5 respectively representing information constrained to 10 hectares and 25 hectares minimum mapping unit. In these two images errors are evident in the form of horizontal lines extending across several adjacent polygons. Again this is related to the procedures responsible of determining the internal region of a polygon (*FindIntExtPolygon()*) section 5.3. The section of the CORINE map corresponding to the geographic co-ordinates of the original classified image is shown in Fig. 7.6.

In chapter 8 the results obtained by the application of the entire generalization process (Geometric and Semantic generalization) are fully discussed and compared to each other.
Fig. 7.2. Raster product obtained by the Automatic Re-labelling Process
Fig. 7.3. Semantically generalized product generated by the expert system responsible for the nomenclature conversion.
Fig. 7.4. Semantically generalized product constrained to the 10 hectares minimum mapping unit
Fig. 7.5. Semantically generalized product constrained to the 25 hectares minimum mapping unit
Fig. 7.6. Section of the CORINE map of Portugal geographically corresponding to the classified image.
7.5 Summary of the Semantic Generalization

The re-organisation of the land use CORINE nomenclature in the Pseudo CORINE land use classes allowed the development of a class-to-class conversion system which is rule-based, objective and therefore suitable for unsupervised and automatic processing. The Pseudo Corine land use nomenclature is compatible with the original CORINE land use scheme, as it contains:

- CORINE land use classes which are automatically recognisable by spectral pattern recognition or by combination of shape and context techniques;
- The CORINE class parent of all CORINE land use classes which are not automatically recognisable from spectral information; and
- Grouping CORINE land use classes which collect together groups of CORINE land use classes which present similar spectral characteristics.

The process responsible for the Automatic Re-labelling of image-classes which present a one-to-one relationship with a single Pseudo Corine land use class is organised as a syntax procedure based on Dictionaries of synonyms of land types categories (image-classes and Pseudo Corine classes) and has been shown to be:

- Objective and generally applicable; and
- Suitable for direct, fast and unsupervised translation.

The automatic conversion of image-classes which present a one-to-many relationship with Pseudo Corine classes performed by the rule-based contextual reasoning is shown to be suitable for unsupervised processing, as:

- Rules allow a precise examination of the spatial and thematic context in which each thematic patch is detected; and
- Hypotheses are contextual allowing the a priori definition of models of context or the surrounding themes (and proportions) for each thematic patch.

The Automatic Merging of Pseudo Corine patches constrained by a minimum mapping unit (MMU) is the final activity of the semantic generalization, which is shown to be essential and sufficient for the generation of a product which satisfies the spatial characteristics of CORINE digital maps (25 hectares MMU) and the generation of a product which is a suitable compromise between the size of the mapped areas and the detail of the CORINE land use nomenclature (10 hectares MMU).
CHAPTER 8 DISCUSSION OF RESULTS

8.1 Introduction

8.2 Input and Target Data

8.3 Classified Image and Geometrically Generalized Image

8.4 Classified Image and Semantically Generalized Image

8.5 Classified Image and Generalized Image of 10 Hectares MMU

8.6 Classified Image and Generalized Image of 25 Hectares MMU

8.7 Semantically Generalized Image and Geometrically Generalized Image

8.8 Semantically Generalized Image and Generalized Image of 10 Hectares MMU

8.9 Semantically Generalized Image and Generalized Image of 25 hectares MMU

8.10 CORINE Map Section and Semantically Generalized Product

8.11 CORINE Map Section and Generalized Image of 25 Hectares MMU

8.12 CORINE Map Section and Generalized Image of 10 Hectares MMU

8.13 Propagation of Error
8.1 Introduction

In this chapter the results of the generalization process are analysed and discussed. The generalization process has produced during its performance several intermediate products which will be examined both individually and in comparison with each other. The products presented in this chapter have already been shown in the previous chapters in association with the description of the processes which generated them. These products are:

1. Geometrically Generalized image (Fig. 6.23);
2. Semantically Generalized image (Fig. 7.3);
3. Generalized image constrained to 10 hectares minimum mapping unit (Fig. 7.4); and
4. Generalized image constrained to 25 hectares minimum mapping unit (Fig. 7.5).

The performance of the generalization process is evaluated via the cross tabulation of the generated products with the original classified image (Fig. 3.9) and the target CORINE map section (Fig. 7.6). Tables and matrices of convergence are presented in this chapter to support and verify the discussed results. Matrices of convergence have been generated with ARC/INFO (1992) facilities and with a purpose built program created by the author in C.

8.2 Input and Target Data

The cross tabulation between the input and the target data for the generalization process is based on the confusion matrix shown in Table 8.1. The classified image (Fig. 3.9) represents 10 land cover classes with the percentages of occupied area as shown in Table 8.2. The section of the CORINE map geographically corresponding to the classified image (Fig. 7.6) represents 7 land use classes with the percentages occupied as shown in Table 8.3. It can be seen that the study area is principally agricultural with two main crops cultivated. Tables 8.4 to 8.10 show the correspondence derived from the confusion matrix between each land use class occurring in the CORINE map section and combinations of land cover classes when the two images are overlaid. Land use class 211 (Non-irrigated arable land) predominates in the CORINE map section, and is associated with land cover class “Grass” for 33.2%, and with land cover class “Soil” for 28.9% of the area occupied by the land use class (Table 8.4).
Land use class 511 (Water courses) is the second (in order of percentages) predominant category in the CORINE map section. This “water” area geographically corresponds with a section of the River Tejo. Comparing the classified image (Fig. 3.9) and the CORINE map section (Fig. 7.6) it may be asserted that the main natural region associated with the land cover class “water” in the classified image and the CORINE polygon associated with the land use class “water courses” in the CORINE map section, match well in their spatial and geometrical characteristics. Considering the fact that the CORINE map and the classified image have been produced by different methods, by different experts and by using different data sources at different times, this 80% of matching land use/land cover pixels, as reported in Table 8.5, may be taken as evidence of the spatial correctness of the classified image. The occurrence of the other land cover classes in low percentages, depends on the minimum shift between the natural boundaries of the river in the classified image and the digitized boundaries in the CORINE map section.

Land use class 112 (Discontinuous urban fabric) occurs in the CORINE map section as the third category of “quantitative” importance. From Table 8.6, more than 50% of the area occupied by the class 112 is associated with the land cover “Urban”. The occurrence of land covers such as “Cereals”, “Forest”, “Vineyard” and “Horticulture” may be used as evidence to assert that “Urban” areas detected in the classified image are rural-urban agglomerations.

Land use class 242 (Complex cultivation patterns) is mainly associated with land cover classes “Grass” and “Soil” which occupy more than 72% of the area of this land use class, as reported in Table 8.7. Land cover class “Horticulture” occupies only 3.7% of this area which is less than the area occupied by the land cover class “Urban” (10.8%). From this information no objective evidence may be extracted for the automatic identification of this area as Complex cultivation patterns.

Land use class 313 (Mixed forest) is associated with land cover classes “Grass” and “Forest” for 81% of the area in the CORINE map section. Land use class 213 (Rice fields) is associated with land cover classes “Soil” and “Aquatic vegetation” for 85% of its area in the CORINE map section. Land cover class 131 (Mineral extraction sites) is associated with land cover classes “Soil” and “Urban” over 64% of its area in the CORINE map section. Automatic identification of the land use “Mineral extraction sites” would be poor from this land cover input.
Table 8.1. The matrix rows show the occurrence, in number of pixels, for each image-class in the classified image (Fig. 3.9); the columns show the occurrence for each CORINE class in the section of the CORINE map (Fig. 7.6) geographically corresponding to the classified image. For each CORINE class occurring in the map section, the combination of image-classes (and occurrence) occupying the same image area is also available in the corresponding column.
## Discussion on Results

<table>
<thead>
<tr>
<th>CLASS</th>
<th>LABEL</th>
<th>TOTAL PIXELS</th>
<th>PERCENTAGE</th>
</tr>
</thead>
<tbody>
<tr>
<td>Soil</td>
<td>1</td>
<td>17643</td>
<td>26.92% of the image area</td>
</tr>
<tr>
<td>Grass</td>
<td>2</td>
<td>20317</td>
<td>31%</td>
</tr>
<tr>
<td>Water</td>
<td>3</td>
<td>4542</td>
<td>6.93%</td>
</tr>
<tr>
<td>Cereals</td>
<td>4</td>
<td>2481</td>
<td>3.8%</td>
</tr>
<tr>
<td>Forest</td>
<td>5</td>
<td>6731</td>
<td>10.27%</td>
</tr>
<tr>
<td>Urban</td>
<td>6</td>
<td>4591</td>
<td>7%</td>
</tr>
<tr>
<td>Vineyard</td>
<td>7</td>
<td>1336</td>
<td>2.04%</td>
</tr>
<tr>
<td>Horticulture</td>
<td>8</td>
<td>6897</td>
<td>10.52%</td>
</tr>
<tr>
<td>Aquatic vegetation</td>
<td>9</td>
<td>813</td>
<td>1.24%</td>
</tr>
<tr>
<td>Marsh</td>
<td>10</td>
<td>185</td>
<td>0.28%</td>
</tr>
</tbody>
</table>

Table 8.2. Land cover classification scheme represented in the classified image (Fig. 3.9). For each class the total number of pixels set to the class in the image and the percentage of the image occupied are reported.

<table>
<thead>
<tr>
<th>CLASS</th>
<th>LABEL</th>
<th>TOT PIXELS</th>
<th>PERCENTAGE</th>
</tr>
</thead>
<tbody>
<tr>
<td>Discontinuous urban fabric</td>
<td>112</td>
<td>881</td>
<td>1.34% of the image area</td>
</tr>
<tr>
<td>Mineral extraction sites</td>
<td>131</td>
<td>25</td>
<td>0.04%</td>
</tr>
<tr>
<td>Non-irrigated arable land</td>
<td>211</td>
<td>58280</td>
<td>88.93%</td>
</tr>
<tr>
<td>Rice fields</td>
<td>213</td>
<td>359</td>
<td>0.55%</td>
</tr>
<tr>
<td>Complex cultivation patterns</td>
<td>242</td>
<td>701</td>
<td>1.07%</td>
</tr>
<tr>
<td>Mixed forest</td>
<td>313</td>
<td>384</td>
<td>0.59%</td>
</tr>
<tr>
<td>(in land) Water courses</td>
<td>511</td>
<td>4906</td>
<td>7.49%</td>
</tr>
</tbody>
</table>

Table 8.3. Land use classes occurring in the CORINE map section (Fig. 7.6) geographically corresponding with the classified image. For each class the total number of pixels set to the class in the map and the corresponding percentage of the image occupied are reported.

**LAND USE CLASS “NON-IRRIGATED ARABLE LAND”**

| land cover Soil     | 16850 pixels | 28.9% of the area occupied by land use 211 |
| land cover Grass    | 19368        | 33.2%                                       |
| land cover Water    | 597          | 1.0%                                        |
| land cover Cereals  | 2210         | 3.8%                                        |
| land cover Forest   | 6451         | 11.1%                                       |
| land cover Urban    | 4007         | 6.9%                                        |
| land cover Vineyard | 1305         | 2.2%                                        |
| land cover Horticulture | 6683    | 11.5%                                       |
| land cover Aqua-Veg.| 671          | 1.2%                                        |
| land cover Marsh    | 138          | 0.2%                                        |

Table 8.4. Land use class 211 and combination of spatially corresponding land cover classes when overlaying the CORINE map section on the classified image.
LAND USE CLASS “WATER COURSES”

<table>
<thead>
<tr>
<th>Land Cover Type</th>
<th>Pixels</th>
<th>Percentage of Area Occupied</th>
</tr>
</thead>
<tbody>
<tr>
<td>Soil</td>
<td>127</td>
<td>2.6%</td>
</tr>
<tr>
<td>Grass</td>
<td>380</td>
<td>7.8%</td>
</tr>
<tr>
<td>Water</td>
<td>3941</td>
<td>80.3%</td>
</tr>
<tr>
<td>Cereals</td>
<td>173</td>
<td>3.5%</td>
</tr>
<tr>
<td>Forest</td>
<td>47</td>
<td>1.0%</td>
</tr>
<tr>
<td>Urban</td>
<td>35</td>
<td>0.7%</td>
</tr>
<tr>
<td>Vineyard</td>
<td>4</td>
<td>0.1%</td>
</tr>
<tr>
<td>Horticulture</td>
<td>145</td>
<td>3.0%</td>
</tr>
<tr>
<td>Aqua-Veg.</td>
<td>34</td>
<td>0.7%</td>
</tr>
<tr>
<td>Marsh</td>
<td>20</td>
<td>0.4%</td>
</tr>
</tbody>
</table>

Total 4906 pixels

Table 8.5. Land use class 511 and combination of spatially corresponding land cover classes when overlaying the CORINE map section on the classified image.

LAND USE CLASS “DISCONTINUOUS URBAN FABRIC”

<table>
<thead>
<tr>
<th>Land Cover Type</th>
<th>Pixels</th>
<th>Percentage of Area Occupied</th>
</tr>
</thead>
<tbody>
<tr>
<td>Soil</td>
<td>193</td>
<td>21.9%</td>
</tr>
<tr>
<td>Grass</td>
<td>123</td>
<td>14.0%</td>
</tr>
<tr>
<td>Water</td>
<td>0</td>
<td>0%</td>
</tr>
<tr>
<td>Cereals</td>
<td>28</td>
<td>3.2%</td>
</tr>
<tr>
<td>Forest</td>
<td>23</td>
<td>2.6%</td>
</tr>
<tr>
<td>Urban</td>
<td>462</td>
<td>52.4%</td>
</tr>
<tr>
<td>Vineyard</td>
<td>22</td>
<td>2.5%</td>
</tr>
<tr>
<td>Horticulture</td>
<td>30</td>
<td>3.4%</td>
</tr>
<tr>
<td>Aqua-Veg.</td>
<td>0</td>
<td>0%</td>
</tr>
<tr>
<td>Marsh</td>
<td>0</td>
<td>0%</td>
</tr>
</tbody>
</table>

Total 881 pixels

Table 8.6. Land use class 112 and combination of spatially corresponding land cover classes when overlaying the CORINE map section on the classified image.

LAND USE CLASS “COMPLEX CULTIVATION PATTERNS”

<table>
<thead>
<tr>
<th>Land Cover Type</th>
<th>Pixels</th>
<th>Percentage of Area Occupied</th>
</tr>
</thead>
<tbody>
<tr>
<td>Soil</td>
<td>222</td>
<td>31.7%</td>
</tr>
<tr>
<td>Grass</td>
<td>285</td>
<td>40.7%</td>
</tr>
<tr>
<td>Water</td>
<td>0</td>
<td>0%</td>
</tr>
<tr>
<td>Cereals</td>
<td>43</td>
<td>6.1%</td>
</tr>
<tr>
<td>Forest</td>
<td>44</td>
<td>6.3%</td>
</tr>
<tr>
<td>Urban</td>
<td>76</td>
<td>10.8%</td>
</tr>
<tr>
<td>Vineyard</td>
<td>5</td>
<td>0.7%</td>
</tr>
<tr>
<td>Horticulture</td>
<td>26</td>
<td>3.1%</td>
</tr>
<tr>
<td>Aqua-Veg.</td>
<td>0</td>
<td>0%</td>
</tr>
<tr>
<td>Marsh</td>
<td>0</td>
<td>0%</td>
</tr>
</tbody>
</table>

Total 701 pixels

Table 8.7. Land use class 242 and combination of spatially corresponding land cover classes when overlaying the CORINE map section on the classified image.
### LAND USE CLASS “MIXED FOREST”

<table>
<thead>
<tr>
<th>Land Cover</th>
<th>Pixels</th>
<th>Percentage of Area Occupied by Land Use 313</th>
</tr>
</thead>
<tbody>
<tr>
<td>Soil</td>
<td>44</td>
<td>11.5%</td>
</tr>
<tr>
<td>Grass</td>
<td>151</td>
<td>39.3%</td>
</tr>
<tr>
<td>Water</td>
<td>0</td>
<td>0%</td>
</tr>
<tr>
<td>Cereals</td>
<td>23</td>
<td>6.1%</td>
</tr>
<tr>
<td>Forest</td>
<td>159</td>
<td>41.4%</td>
</tr>
<tr>
<td>Urban</td>
<td>4</td>
<td>1.0%</td>
</tr>
<tr>
<td>Vineyard</td>
<td>0</td>
<td>0%</td>
</tr>
<tr>
<td>Horticulture</td>
<td>3</td>
<td>0.8%</td>
</tr>
<tr>
<td>Aqua-Veg.</td>
<td>0</td>
<td>0%</td>
</tr>
<tr>
<td>Marsh</td>
<td>0</td>
<td>0%</td>
</tr>
</tbody>
</table>

Total 384 pixels

Table 8.8. Land use class 313 and combination of spatially corresponding land cover classes when overlaying the CORINE map section on the classified image.

### LAND USE CLASS “RICE FIELDS”

<table>
<thead>
<tr>
<th>Land Cover</th>
<th>Pixels</th>
<th>Percentage of Area Occupied by Land Use 213</th>
</tr>
</thead>
<tbody>
<tr>
<td>Soil</td>
<td>198</td>
<td>55.1%</td>
</tr>
<tr>
<td>Grass</td>
<td>6</td>
<td>1.7%</td>
</tr>
<tr>
<td>Water</td>
<td>4</td>
<td>1.1%</td>
</tr>
<tr>
<td>Cereals</td>
<td>0</td>
<td>0%</td>
</tr>
<tr>
<td>Forest</td>
<td>6</td>
<td>1.7%</td>
</tr>
<tr>
<td>Urban</td>
<td>0</td>
<td>0%</td>
</tr>
<tr>
<td>Vineyard</td>
<td>0</td>
<td>0%</td>
</tr>
<tr>
<td>Horticulture</td>
<td>10</td>
<td>2.8%</td>
</tr>
<tr>
<td>Aqua-Veg.</td>
<td>108</td>
<td>30.1%</td>
</tr>
<tr>
<td>Marsh</td>
<td>27</td>
<td>7.5%</td>
</tr>
</tbody>
</table>

Total 359 pixels

Table 8.9. Land use class 213 and combination of spatially corresponding land cover classes when overlaying the CORINE map section on the classified image.

### LAND USE CLASS “MINERAL EXTRACTION SITES”

<table>
<thead>
<tr>
<th>Land Cover</th>
<th>Pixels</th>
<th>Percentage of Area Occupied by Land Use 131</th>
</tr>
</thead>
<tbody>
<tr>
<td>Soil</td>
<td>9</td>
<td>36%</td>
</tr>
<tr>
<td>Grass</td>
<td>4</td>
<td>16%</td>
</tr>
<tr>
<td>Water</td>
<td>0</td>
<td>0%</td>
</tr>
<tr>
<td>Cereals</td>
<td>4</td>
<td>16%</td>
</tr>
<tr>
<td>Forest</td>
<td>1</td>
<td>4%</td>
</tr>
<tr>
<td>Urban</td>
<td>7</td>
<td>28%</td>
</tr>
<tr>
<td>Vineyard</td>
<td>0</td>
<td>0%</td>
</tr>
<tr>
<td>Horticulture</td>
<td>0</td>
<td>0%</td>
</tr>
<tr>
<td>Aqua-Veg.</td>
<td>0</td>
<td>0%</td>
</tr>
<tr>
<td>Marsh</td>
<td>0</td>
<td>0%</td>
</tr>
</tbody>
</table>

Total 25 pixels

Table 8.10. Land use class 131 and combination of spatially corresponding land cover classes when overlaying the CORINE map section on the classified image.
The initial partitioning of the satellite image into closed boundaries performed by Significant Edge Detection (section 4.3) produces an image which is reduced from the original in the number of lines and columns, due to filtering methods used by the partitioning algorithm. The resulting image in fact presents a border on the four sides of the image. Due to the irregular shape of the detected closed boundaries, other pixels along the image borders are excluded (being external to any boundary) from the entire set of the boundary image. In total 1321 pixels were set to "border". The products generated by the generalization process all represent the "boundaries" of main polygons (produced by the Geometric Generalization and occupying 9667 pixels). More details on the derivation of these numbers is given in the last section of this chapter (section 8.13). The sum of border pixels and boundary pixels in the image is thus 10988 "background" pixels. These background pixels are not involved in the discussion presented in the following sections, since they do not represent any land cover class. The association with a land cover class for each boundary pixel, requires a specific study which has not been included in this thesis. For the purposes of this discussion, when comparing the generalized products with the input and/or the target data the percentages presented in the discussion are referred to the set of image pixels reduced by the 10988 "background" pixels. The confusion matrices presented in the following sections, however, allow the reader to recalculate the percentages as desired. Tables 8.2 and 8.3 may then be recalculated with the exclusion of background pixels as shown in Table 8.11 and 8.12.
Discussion on Results

<table>
<thead>
<tr>
<th>CLASS</th>
<th>LABEL</th>
<th>TOTAL PIXELS</th>
<th>PERCENTAGE</th>
</tr>
</thead>
<tbody>
<tr>
<td>Soil</td>
<td>1</td>
<td>14472</td>
<td>26.5% of the image area</td>
</tr>
<tr>
<td>Grass</td>
<td>2</td>
<td>17119</td>
<td>31.4%</td>
</tr>
<tr>
<td>Water</td>
<td>3</td>
<td>4263</td>
<td>7.8%</td>
</tr>
<tr>
<td>Cereals</td>
<td>4</td>
<td>1931</td>
<td>3.5%</td>
</tr>
<tr>
<td>Forest</td>
<td>5</td>
<td>5569</td>
<td>10.2%</td>
</tr>
<tr>
<td>Urban</td>
<td>6</td>
<td>3645</td>
<td>6.7%</td>
</tr>
<tr>
<td>Vineyard</td>
<td>7</td>
<td>1104</td>
<td>2.0%</td>
</tr>
<tr>
<td>Horticulture</td>
<td>8</td>
<td>5663</td>
<td>10.4%</td>
</tr>
<tr>
<td>Aquatic vegetation</td>
<td>9</td>
<td>660</td>
<td>1.2%</td>
</tr>
<tr>
<td>Marsh</td>
<td>10</td>
<td>122</td>
<td>0.2%</td>
</tr>
</tbody>
</table>

Table 8.11. Land cover classification scheme represented in the classified image (Fig. 3.9). For each class the total number of pixels set to the class in the image and the corresponding percentage of occupied area are reported, with respect to the entire image size excluding the background pixels (10988).

<table>
<thead>
<tr>
<th>CLASS</th>
<th>LABEL</th>
<th>TOTAL PIXELS</th>
<th>PERCENTAGE</th>
</tr>
</thead>
<tbody>
<tr>
<td>Discontinuous urban fabric</td>
<td>112</td>
<td>711</td>
<td>1.3% of the image area</td>
</tr>
<tr>
<td>Mineral extraction sites</td>
<td>131</td>
<td>4</td>
<td>0.01%</td>
</tr>
<tr>
<td>Non-irrigated arable land</td>
<td>211</td>
<td>48267</td>
<td>88.5%</td>
</tr>
<tr>
<td>Rice fields</td>
<td>213</td>
<td>324</td>
<td>0.6%</td>
</tr>
<tr>
<td>Complex cultivation patterns</td>
<td>242</td>
<td>511</td>
<td>0.9%</td>
</tr>
<tr>
<td>Mixed forest</td>
<td>313</td>
<td>268</td>
<td>0.5%</td>
</tr>
<tr>
<td>(in land) Water courses</td>
<td>511</td>
<td>4463</td>
<td>8.2%</td>
</tr>
</tbody>
</table>

Table 8.12. Land use classes occurring in the CORINE map section (Fig. 7.6) geographically corresponding with the classified image. For each class the total number of pixels set to the class in the image and the corresponding percentage of occupied area are reported, with respect to the entire image size excluding the background pixels (10988).
8.3 Classified Image and Geometrically Generalized Image

The confusion matrix generated comparing the classified image (Fig. 3.9) and the geometrically generalized product (Fig. 6.23) is shown in Table 8.13, from which one may calculate that 67% of the original distribution of land cover classes has been preserved by the generalization process in the geometrically generalized image. Land cover areas have been emphasised and/or reduced by the process in the percentages presented in Table 8.14.

Comparing Table 8.11 and Table 8.14 the major occurring land cover classes "Soil" and "Grass", have been emphasised respectively by 2.5% and 3.0%, with a corresponding reduction of the other land cover classes. The largest reduction is observed with land cover class "Urban" (1.8% on the total area occupied in the image). It may be concluded that the geometric generalization has simplified the classified image preserving the natural distribution of land cover classes and their proportions.
<table>
<thead>
<tr>
<th>Class</th>
<th>soil</th>
<th>grass</th>
<th>water</th>
<th>cereals</th>
<th>forest</th>
<th>urban</th>
<th>vineyard</th>
<th>horticult</th>
<th>aqua-veg</th>
<th>marsh</th>
<th>bound</th>
<th>bord</th>
</tr>
</thead>
<tbody>
<tr>
<td>soil</td>
<td>12046</td>
<td>1320</td>
<td>9</td>
<td>56</td>
<td>380</td>
<td>254</td>
<td>21</td>
<td>338</td>
<td>46</td>
<td>2</td>
<td>2889</td>
<td>282</td>
</tr>
<tr>
<td>grass</td>
<td>1041</td>
<td>16302</td>
<td>24</td>
<td>76</td>
<td>243</td>
<td>115</td>
<td>6</td>
<td>289</td>
<td>20</td>
<td>3</td>
<td>2899</td>
<td>299</td>
</tr>
<tr>
<td>water</td>
<td>51</td>
<td>212</td>
<td>3932</td>
<td>7</td>
<td>21</td>
<td>1</td>
<td>0</td>
<td>11</td>
<td>6</td>
<td>22</td>
<td>233</td>
<td>46</td>
</tr>
<tr>
<td>cereals</td>
<td>179</td>
<td>231</td>
<td>1308</td>
<td>7</td>
<td>47</td>
<td>11</td>
<td>0</td>
<td>148</td>
<td>0</td>
<td>0</td>
<td>340</td>
<td>210</td>
</tr>
<tr>
<td>forest</td>
<td>491</td>
<td>602</td>
<td>4124</td>
<td>114</td>
<td>212</td>
<td>6</td>
<td>2</td>
<td>1088</td>
<td>74</td>
<td>2</td>
<td>1051</td>
<td>183</td>
</tr>
<tr>
<td>urban</td>
<td>988</td>
<td>315</td>
<td>24</td>
<td>90</td>
<td>2086</td>
<td>2</td>
<td>135</td>
<td>5</td>
<td>0</td>
<td>780</td>
<td>166</td>
<td></td>
</tr>
<tr>
<td>vineyard</td>
<td>226</td>
<td>139</td>
<td>0</td>
<td>45</td>
<td>556</td>
<td>107</td>
<td>20</td>
<td>0</td>
<td>216</td>
<td>16</td>
<td>216</td>
<td>16</td>
</tr>
<tr>
<td>horticulture</td>
<td>676</td>
<td>583</td>
<td>18</td>
<td>84</td>
<td>134</td>
<td>72</td>
<td>12</td>
<td>4069</td>
<td>11</td>
<td>4</td>
<td>1051</td>
<td>183</td>
</tr>
<tr>
<td>aqua-veg</td>
<td>115</td>
<td>47</td>
<td>15</td>
<td>16</td>
<td>0</td>
<td>6</td>
<td>0</td>
<td>460</td>
<td>1</td>
<td>130</td>
<td>23</td>
<td></td>
</tr>
<tr>
<td>marsh</td>
<td>8</td>
<td>18</td>
<td>7</td>
<td>0</td>
<td>3</td>
<td>1</td>
<td>0</td>
<td>24</td>
<td>61</td>
<td>41</td>
<td>41</td>
<td>22</td>
</tr>
</tbody>
</table>

Table 8.13. The matrix rows represent the occurrence, in number of pixels, for each image-class in the classified image (Fig. 3.9); the columns the occurrence for each image-class in the geometrically generalized product (Fig. 6.23). The entries on the principle diagonal of the matrix represent the size of the original clusters in the classified image, which have been emphasised/reduced by the Geometric Generalization.
Discussion on Results

<table>
<thead>
<tr>
<th>CLASS</th>
<th>LABEL</th>
<th>TOT.</th>
<th>PERCENTAGE</th>
<th>DIFFERENCE</th>
</tr>
</thead>
<tbody>
<tr>
<td>Soil</td>
<td>1</td>
<td>15821 pixels</td>
<td>29.00% of the image area</td>
<td>+2.5%</td>
</tr>
<tr>
<td>Grass</td>
<td>2</td>
<td>18769</td>
<td>34.40%</td>
<td>+3.0%</td>
</tr>
<tr>
<td>Water</td>
<td>3</td>
<td>4016</td>
<td>7.36%</td>
<td>-0.4%</td>
</tr>
<tr>
<td>Cereals</td>
<td>4</td>
<td>1561</td>
<td>2.86%</td>
<td>-0.6%</td>
</tr>
<tr>
<td>Forest</td>
<td>5</td>
<td>5102</td>
<td>9.35%</td>
<td>-0.9%</td>
</tr>
<tr>
<td>Urban</td>
<td>6</td>
<td>2664</td>
<td>4.88%</td>
<td>-1.8%</td>
</tr>
<tr>
<td>Vineyard</td>
<td>7</td>
<td>613</td>
<td>1.12%</td>
<td>-0.9%</td>
</tr>
<tr>
<td>Horticulture</td>
<td>8</td>
<td>5309</td>
<td>9.73%</td>
<td>-0.7%</td>
</tr>
<tr>
<td>Aqua-veg</td>
<td>9</td>
<td>598</td>
<td>1.09%</td>
<td>-0.1%</td>
</tr>
<tr>
<td>Marsh</td>
<td>10</td>
<td>95</td>
<td>0.17%</td>
<td>-0.03%</td>
</tr>
</tbody>
</table>

Table 8.14. Land cover classes represented in the geometrically generalized image (Fig. 6.23). For each class the total number of pixels set to the class in the image and the corresponding percentage of the image occupied are reported, with respect to the entire image size excluding the background pixels (10988). The difference from original and final percentages is also shown for each land cover class.

8.4 Classified Image and Semantically Generalized Image

The expert system of the Semantic Generalization performs a rule-based contextual reasoning (section 7.2.2) to automatically convert the land cover areas of the geometrically generalized product into Pseudo Corine (Pcor) land use areas. The generated product (Fig. 7.3) is compared in this section with the classified image (Fig. 3.9). The confusion matrix is shown in Table 8.15 and the original percentages of land cover classes are shown in Table 8.11. Table 8.16 shows in brief the percentages of the image occupied by each Pcor class; one may notice that the major land cover class “Grass” occurring in the classified image has been emphasised as expected by the cartographic generalization, while minor land cover classes “Aquatic vegetation” and “Marsh” have been proportionally reduced in “quantitative importance”. Land cover classes “Cereals” and “Horticulture” have been emphasised due to their natural distribution in the classified image, which is, although noisy, predominant in two well located zones, as shown in Fig. 3.9. Land cover class “Urban”, although occurring with a higher percentage within the classified image (with respect to the classes “Cereals” and “Horticulture”) originally was more fragmented in its distribution, which has determined its subordination to other “more” homogeneous land covers. Land cover classes “Forest” and “Water” are practically stable in their percentages, due to the fact that their distribution was already homogeneous within main polygons.
| Class/Pcor | backg | soil | urban | 11 | 12 | 13 | 14 | 15 | 16 | 17 | 18 | 19 | 20 | 21 | 22 | 23 | 24 | 25 | 26 | 27 | 28 | 29 | 30 | 31 |
|-----------|-------|------|-------|----|----|----|----|----|----|----|----|----|----|----|----|----|----|----|----|----|----|----|----|----|----|----|
| soil      | 3171  | 839  | 9     | 0  | 0  | 0  | 0  | 0  | 515 | 46 | 21 | 2402 | 0  | 380 | 9838 | 0  | 0  | 0  | 0  | 2  | 0  | 0  | 9  | 0  | 0  |
| grass     | 3198  | 137  | 10    | 0  | 0  | 0  | 0  | 0  | 178 | 20 | 6  | 392  | 0  | 243 | 15992 | 0  | 0  | 0  | 0  | 3  | 0  | 0  | 24 | 0  | 0  |
| water     | 279   | 1    | 0     | 0  | 1  | 0  | 0  | 1  | 7  | 6  | 6  | 0  | 13  | 0  | 21  | 259  | 0  | 0  | 0  | 0  | 2  |
| cereals   | 550   | 37   | 1     | 0  | 10 | 0  | 0  | 0  | 1341| 0  | 0  | 174  | 0  | 47  | 314  | 0  | 0  | 0  | 0  |
| forest    | 1162  | 61   | 9     | 0  | 0  | 0  | 0  | 0  | 105 | 0  | 10 | 6   | 10  | 339 | 0   | 1424| 0  | 0  | 0  | 0  | 2  | 0  | 3  |
| urban     | 946   | 94   | 42    | 0  | 2070| 0  | 0  | 89 | 5  | 2  | 317 | 0   | 90  | 35  | 0   | 0   | 0  | 0  | 0  | 0  | 1  |
| vineyard  | 232   | 50   | 0     | 0  | 13 | 0  | 0  | 2  | 1  | 20 | 556 | 124 | 0   | 45  | 294 | 0   | 0  | 0  | 0  | 0  | 0  |
| horticulture | 1234 | 108  | 0     | 98 | 0  | 0  | 171| 11 | 12 | 4173| 0  | 134 | 934 | 0   | 0   | 0  | 0  | 4  | 0  | 0  | 18 | 0  |
| acqua-veg | 153   | 19   | 0     | 0  | 0  | 0  | 0  | 0  | 1  | 460| 6  | 2   | 0   | 15  | 141 | 0   | 0  | 0  | 0  | 0  | 1  | 0  |
| marsh     | 63    | 0    | 0     | 0  | 1  | 0  | 0  | 0  | 24 | 0  | 0  | 0  | 0   | 3   | 0   | 0   | 0  | 0  | 0  | 0  |

Table 8.15. The matrix rows represent the occurrence, in number of pixels, for each image-class in the classified image (Fig. 3.9); the columns the occurrence for each Pcor class in the semantically generalized product (Fig. 7.3). Background pixels are shown in the first column; the occurrence of background pixels originally corresponding to image-classes in the classified image are also shown in the matrix entries of the first column. The presence of image-classes "Soil" and "Urban" in the converted image is explained in the main text of this section.
The 2.6% resulting by the sum of the percentages of the land cover classes “Soil” and “Urban” still occurring in the semantically generalized product, as shown in Table 8.16, may be considered as the error derived from the algorithm \texttt{FindIntExtPoly()} (section 5.3.1 and section 6.6.3) responsible for the detection of the region enclosed by each closed boundary. \texttt{FindIntExtPoly()} in fact does not recognise completely the internal region of certain polygons and generates “holes” in the polygon’s description. The holes are not therefore further analysed by the generalization process since they are “not physically existing areas”. This is the reason why “Soil” and “Urban” areas are still occurring in the generalized product.

8.5 Classified Image and Generalized Image of 10 Hectares MMU

The confusion matrix generated by cross tabulating the classified image (Fig. 3.9) and the generalized product constrained to the minimum mapping unit (MMU) of 10 hectares (Fig. 7.4) is shown in Table 8.17, from which the percentages reported in Table 8.18 have been derived. The generalized product constrained to the 10 hectares MMU represents land use information which has been spatially simplified, with respect to the original, preserving the original themes distribution. This is visually confirmed by comparing the two products.
Discussion on Results

shown in Fig. 3.9 and Fig. 7.4, and the entries (6,12), (4,15), (9,16), (7,17), (8,18), (5,20), (2,21) and (3,29) in the confusion matrix.

Pcor class 29 (Inland water) has been fully preserved and associated with one unique image-object which was originally meaningful in a cartographic context (i.e. large enough to be entirely represented in the final generalized product and thematically homogeneous). The generalization process has recognised the “completeness” of this information and has widely preserved it.

Pcor classes 21 (Natural grassland), 15 (Non-irrigated arable land) and 18 (Heterogeneous agricultural areas) have been globally increased by 33.52%, which mainly derives from the conversion of the land cover class “Soil” and from minor contributions of other Pcor classes which may be calculated from the Table 8.18. Pcor class 26 (Inland wetland) has been completely deleted from the set of land use classes, because its occurrence did not satisfy the threshold of 10 hectares.

Other Pcor classes, 12, 16, 17 and 20 (respectively corresponding to land cover classes 6, 9, 7 and 5), have been reduced proportionally to their original characteristics, quantitatively (occurrence) and qualitatively (spatial distribution), as required by an objective generalization activity.
Table 8.17. The matrix rows represent the occurrence, in number of pixels, for each image-class in the classified image (Fig. 3.9); the column the occurrence for each Pcor class in the semantically generalized product constrained to 10 hectares MMU (Fig. 7.4). Background pixels are shown in the first column; the occurrence of background pixels originally corresponding to image-classes in the classified image are also shown in the matrix entries of the first column.


<table>
<thead>
<tr>
<th>CLASS</th>
<th>LABEL</th>
<th>TOT.</th>
<th>PERC.</th>
<th>DIFFERENCE</th>
</tr>
</thead>
<tbody>
<tr>
<td>Land cover classes</td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Soil</td>
<td>1</td>
<td>1346 pixels</td>
<td>2.47% of the image</td>
<td></td>
</tr>
<tr>
<td>Urban</td>
<td>6</td>
<td>71</td>
<td>0.13%</td>
<td></td>
</tr>
<tr>
<td>Pcor classes</td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Discont. urban fabric</td>
<td>12</td>
<td>1086</td>
<td>1.99%</td>
<td>-4.69%</td>
</tr>
<tr>
<td>Non-irrig. arable land</td>
<td>15</td>
<td>2084</td>
<td>3.82%</td>
<td>stable</td>
</tr>
<tr>
<td>Rice fields</td>
<td>16</td>
<td>448</td>
<td>0.82%</td>
<td>-0.39%</td>
</tr>
<tr>
<td>Vineyard</td>
<td>17</td>
<td>148</td>
<td>0.27%</td>
<td>-1.75%</td>
</tr>
<tr>
<td>Heterog. agri. areas</td>
<td>18</td>
<td>7339</td>
<td>13.45%</td>
<td>+3.07%</td>
</tr>
<tr>
<td>Forest</td>
<td>20</td>
<td>4521</td>
<td>8.29%</td>
<td>-1.92%</td>
</tr>
<tr>
<td>Natural grassland</td>
<td>21</td>
<td>33587</td>
<td>61.57%</td>
<td>+30.17%</td>
</tr>
<tr>
<td>Inland Wetlands</td>
<td>26</td>
<td>0</td>
<td>0%</td>
<td>deleted</td>
</tr>
<tr>
<td>Inland water bodies</td>
<td>29</td>
<td>3918</td>
<td>7.18%</td>
<td>-0.64%</td>
</tr>
</tbody>
</table>

Table 8.18. Pcor land use classes represented in the Semantically Generalized image constrained to the 10 hectares MMU (Fig. 7.4). For each class the total number of pixels set to the class in the image and the corresponding percentage of the image occupied are reported, with respect to the entire image size excluding background pixels (10988). The difference from original and final percentages is also shown between Pcor classes and the directly related land cover classes.

8.6 Classified Image and Generalized Image of 25 Hectares MMU

The confusion matrix generated by cross tabulating the classified image (Fig. 3.0) and the generalized product constrained to a minimum mapping unit (MMU) of 25 hectares (Fig. 7.5) is shown in Table 8.19, from which the percentages reported in Table 8.20 have been derived. It may be calculated that Pcor classes 21 (Natural grassland) and 18 (Heterogeneous agricultural areas) have been globally increased by 40%, which mainly derives from the conversion of the land cover class “Soil”. Minor contributions from other Pcor classes may be seen in Table 8.20.

As already noted in the product constrained to the 10 hectares MMU, from the confusion matrix the conclusion arises that Pcor classes 29 (Inland water bodies), 21 (Natural grass), 20 (Forests), 18 (Heterogeneous agricultural areas) and 15 (Non-irrigated arable land) have been emphasised in the area where they were originally more predominant. This may be easily confirmed by looking in the matrix at the co-ordinates (4,15), (8,18), (5,20), (2,21) and (3,29) which represent the major contributions to each Pcor land use class. The product constrained to the 25 hectares MMU is, as expected, more homogeneous then the 10 hectares
MMU product (Fig. 7.4), but still represents the original characteristics (with respect to the classified image).

This achievement in preserving original characteristics is due to the combined success of:

- The contextual merging and the smoothing process of the Geometric Generalization (which operates consistently on the general distribution of each original land cover area); and

- The automatic relabelling process (which directly converts pixels from the image-class to the corresponding Pcor class); the hypothesis verification process (which operates consistently on the major distribution of each original land cover areas and already converted Pcor land use areas); and the contextual merging of the Semantic Generalization (during the production of the 25 hectares MMU image).
| Class/Pcor | back | soil | urban | 11 | 12 | 13 | 14 | 15 | 16 | 17 | 18 | 19 | 20 | 21 | 22 | 23 | 24 | 25 | 26 | 27 | 28 | 29 | 30 | 31 |
|-----------|------|------|-------|----|----|----|----|----|----|----|----|----|----|----|----|----|----|----|----|----|----|----|----|----|----|
| soil      | 3171 | 839 | 9     | 0  | 4  | 0  | 0  | 389| 0  | 0  | 2261| 0  | 273 | 10888| 0  | 0  | 0  | 0  | 0  | 0  | 0  | 0  | 9  | 0  | 0  |
| grass     | 3198 | 137 | 10    | 0  | 3  | 0  | 0  | 327| 1  | 0  | 713 | 0  | 222 | 15682| 0  | 0  | 0  | 0  | 0  | 0  | 0  | 0  | 24 | 0  | 0  |
| water     | 279  | 1    | 0     | 0  | 0  | 0  | 0  | 18 | 0  | 0  | 62  | 0  | 13  | 334  | 0  | 0  | 0  | 0  | 0  | 0  | 0  | 0  | 3835| 0  | 0  |
| cereals   | 550  | 37   | 1     | 0  | 0  | 0  | 0  | 717| 0  | 0  | 306 | 0  | 30  | 833  | 0  | 0  | 0  | 0  | 0  | 0  | 0  | 0  | 7   | 0  | 0  |
| forest    | 1162 | 61   | 9     | 0  | 0  | 0  | 0  | 96 | 0  | 0  | 603 | 0  | 1525| 3272 | 0  | 0  | 0  | 0  | 0  | 0  | 0  | 0  | 3   | 0  | 0  |
| urban     | 946  | 94   | 42    | 0  | 1  | 0  | 0  | 132| 0  | 0  | 684 | 0  | 15  | 2676 | 0  | 0  | 0  | 0  | 0  | 0  | 0  | 0  | 1   | 0  | 0  |
| vineyard  | 232  | 50   | 0     | 0  | 17 | 0  | 0  | 31 | 0  | 0  | 47  | 0  | 1   | 958  | 0  | 0  | 0  | 0  | 0  | 0  | 0  | 0  | 0   | 0  | 0  |
| horticulture | 1234 | 108 | 0     | 0  | 22 | 0  | 0  | 198| 0  | 0  | 2691| 0  | 184 | 2442 | 0  | 0  | 0  | 0  | 0  | 0  | 0  | 0  | 18  | 0  | 0  |
| aqua-veg  | 153  | 19   | 0     | 0  | 0  | 0  | 0  | 0  | 1  | 0  | 0  | 619 | 0  | 0   | 0  | 0  | 0  | 0  | 0  | 0  | 0  | 14  | 0  | 0  |
| marsh     | 63   | 0    | 0     | 0  | 0  | 0  | 0  | 1  | 0  | 1  | 0  | 7   | 113 | 0  | 0  | 0  | 0  | 0  | 0  | 0  | 0  | 7   | 0  | 0  |

Table 8.19. The matrix rows represent the occurrence, in number of pixels, for each image-class in the classified image (Fig. 3.9); the column the occurrence for each Pcor class in the semantically generalized product constrained to 25 hectares MMU (Fig. 7.5). Background pixels are shown in the first column; the occurrence of background pixels originally corresponding to image-classes in the classified image are also shown in the matrix entries of the first column.
Table 8.20. Pcor land use classes represented in the Semantically Generalized image constrained to the 25 hectares MMU (Fig. 7.5). For each class the total number of pixels set to the class in the image and the corresponding percentage of the image occupied are reported, with respect to the entire image size excluding background pixels (10988). The difference from original and final percentages is also shown between Pcor classes and the directly related land cover classes.

<table>
<thead>
<tr>
<th>CLASS</th>
<th>LABEL</th>
<th>TOT.</th>
<th>PERC.</th>
<th>DIFFERENCE</th>
</tr>
</thead>
<tbody>
<tr>
<td>Land cover classes</td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Soil</td>
<td>1</td>
<td>1346</td>
<td>2.47%</td>
<td></td>
</tr>
<tr>
<td>Urban</td>
<td>6</td>
<td>71</td>
<td>0.13%</td>
<td></td>
</tr>
<tr>
<td>Pcor classes</td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Discont. urban fabric</td>
<td>12</td>
<td>47</td>
<td>0.09%</td>
<td>-6.59%</td>
</tr>
<tr>
<td>Non-irrig. arable land</td>
<td>15</td>
<td>1908</td>
<td>3.50%</td>
<td>stable</td>
</tr>
<tr>
<td>Rice fields</td>
<td>16</td>
<td>2</td>
<td>0.004%</td>
<td>-1.43%</td>
</tr>
<tr>
<td>Vineyard</td>
<td>17</td>
<td>0</td>
<td>0%</td>
<td>-2.02%</td>
</tr>
<tr>
<td>Heterog. agri. areas</td>
<td>18</td>
<td>7369</td>
<td>13.5%</td>
<td>+3.12%</td>
</tr>
<tr>
<td>Forest</td>
<td>20</td>
<td>2270</td>
<td>4.16%</td>
<td>-6.05%</td>
</tr>
<tr>
<td>Natural grassland</td>
<td>21</td>
<td>37617</td>
<td>68.96%</td>
<td>+37.56%</td>
</tr>
<tr>
<td>Inland Wetlands</td>
<td>26</td>
<td>0</td>
<td>0%</td>
<td>already</td>
</tr>
<tr>
<td>Inland water bodies</td>
<td>29</td>
<td>3918</td>
<td>7.18%</td>
<td>-0.64%</td>
</tr>
</tbody>
</table>

8.7 Semantically Generalized Image and Geometrically Generalized Image

The confusion matrix generated by cross tabulating the product generated by the Semantic Generalization (Fig. 7.3) and the product generated by the Geometric Generalization (Fig. 6.23) is shown in Table 8.21. From the matrix and from the images of the two products it may be noted that land cover classes have been converted and spatially emphasised in their original locations, and are respectively compatible with their context. In fact, for each incremented land use area, the increment (with respect to the corresponding land cover) is due to the land cover “Soil”. It may thus be concluded that the Semantic Generalization worked consistently with the original spatial and thematic context of the data to be converted.
Table 8.21. The matrix rows represent the result of the nomenclature conversion performed by the Semantic Generalization (Fig. 7.3); columns the geometrically generalized product (Fig. 6.23) before conversion. The total area in the geometrically generalized product occupied by the image-class "Soil" has been contextually decomposed and converted into several Pcor classes.
8.8 Semantically Generalized Image and Generalized Image of 10 Hectares MMU

The confusion matrix generated by cross tabulating the semantically generalized product (Fig. 7.3) and the final image constrained to the MMU of 10 hectares (Fig. 7.4) is shown in Table 8.22 from which the percentages for each Pcor class, shown in Table 8.23, is derived. Each Pcor class has been emphasised in the original location, as is evident from the confusion matrix. The product generated by the Semantic Generalization has also been smoothed in proportion to the occurrence of each class, as confirmed from table 8.23. One exception is Pcor class 12 (Discontinuous urban fabric) which due to the distribution in several small (although homogeneous) areas has been greatly reduced. Pcor class 26 (Inland wetlands) occurred in the semantically generalized product as an area covering only 0.17% of the image area (excluding background pixels). Pcor class 26 has therefore not been preserved in the final product by the generalization process since it does not satisfy the threshold of 10 hectares, which corresponds to 111 pixels, i.e. 0.2% of the image area (excluding background pixels).
Table 8.22. The matrix rows represent the result of the nomenclature conversion performed on the geometrically generalized product (Fig. 7.3) by the Semantic Generalization; the columns the semantically generalized product constrained to the 10 hectares MMU (Fig. 7.4). The principle diagonal of the matrix shows the original clusters of Pcor classes which have been emphasised/reduced once constrained to the MMU.
8.9 Semantically Generalized Image and Generalized Image of 25 hectares MMU

The confusion matrix generated by cross tabulation of the semantically generalized product (Fig. 7.3) and the generalized image constrained to the MMU of 25 hectares (Fig. 7.5) is shown in Table 8.24 from which the percentages relating to each Pcor class, and shown in Table 8.25, are derived. The percentage difference of the Pcor class 29 (Inland water bodies) between the two images is due to the occurrence of 98 “noisy” pixels in the form of lines of Pcor class 21 and 18 in the polygon “water”. This noise must be considered as error propagated by the procedure FindIntExtPoly() as described in sections 5.3.1 and 6.6.3. This error, however, corresponds to only 0.2% of the entire image and does not preclude an objective analysis of the generalization process.

In the discussion which follows, one should remember the relationship between the minimum mapping unit and the corresponding percentage over the image size excluding background pixels which is:

\[
25 \text{ hectares} \equiv 278 \text{ pixels} \equiv 0.5\% \text{ of the whole image}
\]

Pcor class 26 (Inland wetland) has not been preserved in the final image since it does not cover 0.5% of the image (corresponding to the MMU of 25 hectares). Pcor class 17

<table>
<thead>
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<th>GENERALIZED PRODUCT</th>
<th>FINAL 10 HE. MMU IMAGE</th>
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<tbody>
<tr>
<td>Pcor 21 = 54.30% of the image</td>
<td>Pcor 21 = 61.57% of the image</td>
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<td>Pcor 18 = 14.60%</td>
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<td>Pcor 20 = 9.40%</td>
<td>Pcor 20 = 8.29%</td>
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<td>Pcor 29 = 7.40%</td>
<td>Pcor 29 = 7.18%</td>
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<td>Pcor 12 = 5.20%</td>
<td>Pcor 12 = 1.99%</td>
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<tr>
<td>Pcor 15 = 4.20%</td>
<td>Pcor 15 = 3.82%</td>
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<tr>
<td>Pcor 16 = 1.10%</td>
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<tr>
<td>Pcor 17 = 1.10%</td>
<td>Pcor 17 = 0.27%</td>
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<tr>
<td>Pcor 26 = 0.17%</td>
<td>Pcor 26 = 0%</td>
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Table 8.23. Percentages of the image occupied associated to each Pcor class in the semantically generalized product and the final representation constrained to 10 hectares MMU. Percentages are referred to the image size excluding background pixels (10988).
(Vineyards), although occupying an area which is 1.1% of the entire image (excluding background pixels), is distributed within many polygons in small proportions (Fig. 3.9) which individually cannot survive the generalization. Similarly Pcor classes 16 (Rice fields), 20 (Forests), 15 (Non-irrigated arable land) and 12 (Discontinuous urban fabric) do not survive the cut-off of 25 hectares MMU because of their distribution within many polygons.

Pcor class 29 (Inland water bodies) has been entirely preserved in geometry and proportion. Pcor class 18 (Heterogeneous agricultural areas) has been preserved in the final image and has also being emphasised in the two main areas where it predominates, covering 6.5% of the entire image. Pcor class 21 (Natural grass) is the major land use class in the generalized product and as expected has been greatly emphasized in the final generalized image.
Table 8.24. The matrix rows represent the result of the nomenclature conversion performed on the geometrically generalized product (Fig. 7.3) by the Semantic Generalization; the columns the semantically generalized product constrained to the 25 hectares MMU (Fig. 7.5). The principle diagonal of the matrix shows the original clusters of Pcor classes which have been emphasised/reduced once constrained to the MMU.
GENERALIZED PRODUCT | FINAL 25 HE. MMU IMAGE
---|---
Pcor 21 = 54.3% of the image | Pcor 21 = 68.96% of the image
Pcor 18 = 14.6% | Pcor 18 = 13.5%
Pcor 20 = 9.4% | Pcor 20 = 4.16%
Pcor 29 = 7.4% | Pcor 29 = 7.18%
Pcor 12 = 5.2% | Pcor 12 = 0.09%
Pcor 15 = 4.2% | Pcor 15 = 3.5%
Pcor 16 = 1.1% | Pcor 16 = 0.004%
Pcor 17 = 1.1% | Pcor 17 = 0%
Pcor 26 = 0.17% | Pcor 26 = 0%

Table 8.25. Percentages of the image occupied associated to each Pcor class in the semantically generalized product and the final representation constrained to 25 hectares MMU. Percentages are referred to the image size excluding background pixels (10988).

8.10 CORINE Map Section and Semantically Generalized Product

The confusion matrix derived from the combination of the CORINE map section (Fig. 7.6) and the semantically generalized product (Fig. 7.3) is shown in Tables 8.26a and 8.26b. It is important to notice that the Pcor land use class 16 (Rice fields) exists in the generalized image with 598 pixels, i.e. 1.1% of the entire image (excluding background pixels). In the CORINE map section the area globally occupied by the land use class 213 (Rice fields) is only 0.55 % (359 pixels) of the map area (excluding background pixels) which is much smaller than the percentage of the corresponding Pcor class 16. Similar comparisons may be made for Pcor class 12 (Discontinuous urban fabric) which occupies an area of 2823 pixels corresponding to 5.18% of the converted image area. In the CORINE map section the class 112 (Discontinuous urban fabric) occupies an area of 881 pixels, i.e. 1.34% of the image area, which is much smaller than the percentage of the corresponding Pcor class 12.

Overlaying the two products (Fig. 7.3 and Fig. 7.6) it may be noticed that only two specific regions have been chosen to represent respectively the CORINE class 112 (Discontinuous urban fabric) and the class 213 (Rice fields), which spatially and proportionally match with the underlying Pcor areas 12 (Discontinuous urban fabric) and 16 (Rice fields). Looking at the entire CORINE map shown in Fig. 2.3 it can be seen that those two particular areas do not belong to more extended areas of the same class in the CORINE map. This means that the CORINE expert has used other knowledge supporting the decision
to map these two specific areas rather than others. For example, the use of agricultural maps and cadastral maps, showing "politically" important cultivation and rural-urban distributions might have been used.

For the research conducted for this thesis, a topographic map and an agriculture-forest map were available for the geographical region under analysis, and shown in Fig. 8.1 through Fig. 8.4. Those maps are dated (1951/1963-1977) but clearly show the derivation of the CORINE map from similar sources. On these maps in fact an important "area social" is reported named Castanheira do Ribatejo, geographically corresponding with the "Discontinuous urban fabric" area emphasised in the CORINE map section. Similar consideration may be made for the land cover class "Rice fields". The information provided by the two maps has not been integrated in the information provided to the generalization process due to the huge difference in date of production.
Table 8.26a. The matrix rows represent the occurrence, in number of pixels, for each CORINE class in the CORINE map section under study (Fig. 7.6); and columns the occurrence for each Pcor class in the semantically generalized product (Fig. 7.3). For each CORINE class occurring in the map section is also available, represented in the corresponding column, the combination of Pcor classes occurring in the image in the same geographic area occupied by the specific CORINE class.
### Table 8.26b

The matrix rows represent the occurrence, in number of pixels, for each CORINE class in the CORINE map section under study (Fig. 7.6); and columns the occurrence for each Pcor class in the semantically generalized product (Fig. 7.3). For each CORINE class occurring in the map section is also available, represented in the corresponding column, the combination of Pcor classes occurring in the image in the same geographic area occupied by the specific CORINE class.

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Fig. 8.1. Section of the topographic map of Portugal containing the area represented in the classified image (Fig. 3.9). The topographic map belongs to the Istituto Geographico e Cadastral de Portugal. Description of the map:

"Carta de Portugal 1:100.000
Torres Vedras Fl. 30
Série M684 Edição 1-IGCP
LC077100PT01 Torres Vedras 30 Topographic
Desenhada e publicata pelo Istituto Geografico e Cadastral em 1977"
### Discussion on Results

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<th>Caminhos municipais e outros</th>
<th>Caminho vicinal</th>
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- Caminhos de ferro
  - Areal e dunas
  - Linha de altezação (00KV ou mais)
  - Central elétrica

### Passagens nos rios

- Passagens inferior
- Passagens superior

### Linha de água

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<th>Légs ou albufeira</th>
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<th>Aqueduto subterrâneo</th>
<th>Marinha</th>
<th>Poço, Aeromotor, Nosa</th>
<th>Nascente, Fonte, Chafariz</th>
<th>Tanque, Azenha, Depósito elevado</th>
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### Porto, Aeroporto, Nosa

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<th>Tanque, Azenha, Depósito elevado</th>
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<td>Nascente, Fonte, Chafariz</td>
<td>Tanque, Azenha, Depósito elevado</td>
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<td>Poço, Aeromotor, Nosa</td>
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### Série M 684

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### Torres Vedra

- Sede: de distrito
- Sede: de freguesia
- Outras possibilidades

### Designações locais

Fig. 8.2. Legend for the section of topographic map of Portugal shown in Fig. 1.
Fig. 8.3. Section of the “Carta Agricola e Forestal” of Portugal containing the area represented in the classified image (Fig. 3.9). The map belongs to the “Ministero da Economia de Portugal – Secretaria de Estado da Agricultura”.

Description of the map:

“Servicio de Reconhecimento e de Ordenamento Agrario
Carta Agricola e Florestal de Portugal – 390
LC051025PT02
Escala 1:25.000
Reconhecimento de campo: 1951 – Actualização: 1963”
### Discussion on Results

**Olivel, Figueiral**

Cultures arvenses de regedio

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Povoamenlo egro-floreslel

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<td>Vmhe</td>
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**Figural**

Area social

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**Povoamenlo floreslel**

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**Povoamenlo decrepitos ou caducos**

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<th>Povoamenlo floreslel</th>
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<td>Aveleira</td>
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**Planlagoes ou Povoamen/os**

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<th>Arvores em bordedura</th>
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<td>Indicegao de dom inincia</td>
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*Fig. 8.4. Legend for the section of “Carta Agricula e Forestal” of Portugal shown in Fig. 3.*
8.11 CORINE Map Section and Generalized Image of 25 Hectares MMU

The cross tabulation generated by the combination of the CORINE map section (Fig. 7.6) and the generalized product constrained to 25 hectares MMU (Fig. 7.5) is shown in Tables 8.27a and 8.27b. From this and from Table 8.3 the following observations are derived and illustrated in Table 8.28.

Excluding the Pcor land use 21 (Natural grassland), which is discussed below, the ordering of Pcor land use classes in the generalized product corresponds to the ordering of CORINE land use classes in the CORINE map section, as shown in Table 8.28. Obviously a direct comparison between the specific percentage values would not be useful due to the different methods used to derive land use information and due to the different times of production.

In detail, the CORINE map section presents a very high percentage of land use class 211 (Non-irrigated arable land) and a very low percentage of land use 242 (Complex cultivation patterns). In contrast, the final product of the generalization process generalized to the 25 hectares MMU presents a higher percentage of Pcor class 18 (Heterogeneous agricultural areas) which corresponds with the CORINE class 242, and a lower percentage of Pcor class 15 (Non-irrigated arable land) corresponding with the CORINE class 211. This difference may be due to the different time of sensing of the sources used to create the two products: it is common in fact in agriculture to rotate crops in the cultivation system.

A “water course” occurs in both the products, as respectively CORINE class 511 and Pcor class 29, with similar percentages and in the same geographical area. CORINE classes 112 (Discontinuous urban fabric), 213 (Rice fields) and 313 (Mixed forest) and the corresponding Pcor classes 12, 16 and 20 all match as minor categories. The difference in percentages among those categories in the CORINE map section and in the generalized product, is due to the fact that the CORINE map section has been “cut” from an already generalized product, while the generalization process has worked on a 256x256 image section, referring to this image section for establishing global and individual percentages. In fact, the CORINE class 131 (Mineral extraction sites) represented in the CORINE map section with only 25 pixels, is part of a more extended area in the full CORINE map.

Particular attention needs to be paid to Pcor class 21 (Natural grasslands). This category represents the predominant land use in the generalized product. As well known by
phenologists, the recurring, and specific changes of crops through the seasons, climatic, atmospheric or geographic conditions may provide useful information in distinguishing crops types during image analysis (Chapter 2). Depending on the time of the year, a “Non-irrigated arable land” (Pcor 15 or CORINE 211) may assume several aspects spectrally similar to those of a grass field detected in different phenological phases:

1. Bare soil, when the field has just been ploughed or prior to “seeding”;
2. Mixed between grass and bare soil, when the plants are small, following germination; and
3. Homogeneous green, when the plants are taller and larger.

In this context, it may then be concluded that the generalized product matches in land types with the target CORINE map section and may be directly compared with it in GIS environment.

As already explained in Chapter 3, for this research one single-date classified image has been allowed, excluding the possibility for multi-temporal analysis. However, information concerning crop types, phenological calendars (phases) and calendars of the agriculture practices specific for the area of interest, if available, reliable and updated, might be used by the expert system in alternative to the analysis of several classified images. An example of information system collecting this type of information is reported in Narciso et al., 1992.
Table 8.27a. The matrix rows represent the occurrence, in number of pixels, for each CORINE class in the CORINE map section under study (Fig. 7.6); and columns the occurrence for each Pcor class in the semantically generalized product constrained to the 25 hectares MMU (Fig. 7.5). For each CORINE class occurring in the map section is also available, represented in the corresponding column, the combination of Pcor classes occurring in the image in the same geographic area occupied by the specific CORINE class.
Table 8.27b. The matrix rows represent the occurrence, in number of pixels, for each CORINE class in the CORINE map section under study (Fig. 7.6); and columns the occurrence for each Pcor class in the semantically generalized product constrained to the 25 hectares MMU(Fig. 7.5). For each CORINE class occurring in the map section is also available, represented in the corresponding column, the combination of Pcor classes occurring in the image in the same geographic area occupied by the specific CORINE class.
8.12 CORINE Map Section and Generalized Image of 10 Hectares MMU

The cross tabulation of the CORINE map section (Fig. 7.6) and the generalized product constrained to 10 hectares MMU (Fig. 7.4) is shown in Tables 8.29a and 8.29b. From the confusion matrix and from Table 8.3 observations similar to the ones presented for the product constrained to the 25 hectares MMU are derived and illustrated in Table 8.30.

Differences between the product constrained to the 10 hectares MMU and the one constrained to the 25 hectares MMU are quantified in the confusion matrix shown in Table 8.31. By inspecting the two constrained products (Fig. 7.4 and Fig. 7.5) and the CORINE map section (Fig. 7.6), it may be noticed that the detail occurring in the 10 hectares product ("Discontinuous urban fabric" and "Forest") which did not survive in the 25 hectares product, partially corresponds to the information represented in the CORINE map. This may suggest that "subjective" decisions derived by a human expert have been made during the production of the CORINE map. It may be concluded that the 10 hectares product is, however, thematically and spatially compatible with the CORINE map section and it may be directly used as GIS input.
Table 8.29a. The matrix rows represent the occurrence, in number of pixels, for each CORINE class in the CORINE map section under study (Fig. 7.6); and columns the occurrence for each Pcor class in the semantically generalized product constrained to the 10 hectares MMU(Fig. 7.4). For each CORINE class occurring in the map section is also available, represented in the corresponding column, the combination of Pcor classes occurring in the image in the same geographic area occupied by the specific CORINE class.
Table 8.29b. The matrix rows represent the occurrence, in number of pixels, for each CORINE class in the CORINE map section under study (Fig. 7.6); and columns the occurrence for each Pcor class in the semantically generalized product constrained to the 10 hectares MMU (Fig. 7.4). For each CORINE class occurring in the map section is also available, represented in the corresponding column, the combination of Pcor classes occurring in the image in the same geographic area occupied by the specific CORINE class.
### Discussion on Results

Table 8.30. Percentages of image occupied by CORINE classes in the CORINE map section and by Pcor classes in the 10 MMU generalized product. Percentages are referred to the image size excluding background pixels (10988).

In short: (Pcor classes) \(21 + 15 + 18 = 78.84\%\) & \(211 + 242 + 321\) (CORINE classes) = \(89\%\)

<table>
<thead>
<tr>
<th>CORINE map section</th>
<th>GENERALIZED PRODUCT 10-hectares</th>
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<tbody>
<tr>
<td>211+242 = 89.0%</td>
<td>15+18 = 17.27%</td>
</tr>
<tr>
<td>511 = 8.0%</td>
<td>29 = 7.18%</td>
</tr>
<tr>
<td>112 = 1.3%</td>
<td>12 = 1.99%</td>
</tr>
<tr>
<td>213 = 0.6%</td>
<td>16 = 0.82%</td>
</tr>
<tr>
<td>313 = 0.5%</td>
<td>20 = 8.29%</td>
</tr>
<tr>
<td>131 = 0.01%</td>
<td>13 = 0%</td>
</tr>
<tr>
<td>321 = 0%</td>
<td>21 = 61.57%</td>
</tr>
<tr>
<td>221 = 0%</td>
<td>17 = 0.27%</td>
</tr>
</tbody>
</table>

**Legend of Class names (CORINE - Pcor)**

- 211 = non-irrigated arable land
- 242 = complex cultivation patterns
- 511 = water courses
- 112 = discontinuous urban fabric
- 213 = rice fields
- 313 = mixed forest
- 131 = mineral extraction sites
- 321 = natural grassland
- 221 = vineyards

15 = non-irrigated arable land
18 = heterogeneous agricultural areas
29 = inland water bodies
12 = discontinuous urban fabric
16 = rice fields
13 = forest
13 = construction sites
21 = natural grassland
17 = vineyards
| Pcor/Pcor | back | soil | urban | 11    | 12    | 13    | 14    | 15    | 16    | 17    | 18    | 19    | 20    | 21    | 22    | 23    | 24    | 25    | 26    | 27    | 28    | 29    | 30    | 31    |
|-----------|------|------|-------|-------|-------|-------|-------|-------|-------|-------|-------|-------|-------|-------|-------|-------|-------|-------|-------|-------|-------|-------|-------|-------|-------|-------|
| border 0  | 10988| 0    | 0     | 0     | 0     | 0     | 0     | 0     | 0     | 0     | 0     | 0     | 0     | 0     | 0     | 0     | 0     | 0     | 0     | 0     | 0     | 0     | 0     | 0     |
| soil      | 0    | 1346 | 0     | 0     | 0     | 0     | 0     | 0     | 0     | 0     | 0     | 0     | 0     | 0     | 0     | 0     | 0     | 0     | 0     | 0     | 0     | 0     | 0     | 0     |
| urban     | 0    | 0    | 71    | 0     | 0     | 0     | 0     | 0     | 0     | 0     | 0     | 0     | 0     | 0     | 0     | 0     | 0     | 0     | 0     | 0     | 0     | 0     | 0     | 0     |
| 11        | 0    | 0    | 0     | 0     | 0     | 0     | 0     | 0     | 0     | 0     | 0     | 0     | 0     | 0     | 0     | 0     | 0     | 0     | 0     | 0     | 0     | 0     | 0     | 0     |
| 12        | 0    | 0    | 0     | 0     | 0     | 0     | 0     | 0     | 0     | 0     | 0     | 0     | 0     | 0     | 0     | 0     | 0     | 0     | 0     | 0     | 0     | 0     | 0     | 0     |
| 13        | 0    | 0    | 0     | 0     | 0     | 0     | 0     | 0     | 0     | 0     | 0     | 0     | 0     | 0     | 0     | 0     | 0     | 0     | 0     | 0     | 0     | 0     | 0     | 0     |
| 14        | 0    | 0    | 0     | 0     | 0     | 0     | 0     | 0     | 0     | 0     | 0     | 0     | 0     | 0     | 0     | 0     | 0     | 0     | 0     | 0     | 0     | 0     | 0     | 0     |
| 15        | 0    | 0    | 0     | 0     | 0     | 0     | 0     | 0     | 0     | 0     | 0     | 0     | 0     | 0     | 0     | 0     | 0     | 0     | 0     | 0     | 0     | 0     | 0     | 0     |
| 16        | 0    | 0    | 0     | 0     | 0     | 0     | 0     | 0     | 0     | 0     | 0     | 0     | 0     | 0     | 0     | 0     | 0     | 0     | 0     | 0     | 0     | 0     | 0     | 0     |
| 17        | 0    | 0    | 0     | 0     | 0     | 0     | 0     | 0     | 0     | 0     | 0     | 0     | 0     | 0     | 0     | 0     | 0     | 0     | 0     | 0     | 0     | 0     | 0     | 0     |
| 18        | 0    | 0    | 0     | 0     | 0     | 0     | 0     | 0     | 0     | 0     | 0     | 0     | 0     | 0     | 0     | 0     | 0     | 0     | 0     | 0     | 0     | 0     | 0     | 0     |
| 19        | 0    | 0    | 0     | 0     | 0     | 0     | 0     | 0     | 0     | 0     | 0     | 0     | 0     | 0     | 0     | 0     | 0     | 0     | 0     | 0     | 0     | 0     | 0     | 0     |
| 20        | 0    | 0    | 0     | 0     | 0     | 0     | 0     | 0     | 0     | 0     | 0     | 0     | 0     | 0     | 0     | 0     | 0     | 0     | 0     | 0     | 0     | 0     | 0     | 0     |
| 21        | 0    | 0    | 0     | 0     | 0     | 0     | 0     | 0     | 0     | 0     | 0     | 0     | 0     | 0     | 0     | 0     | 0     | 0     | 0     | 0     | 0     | 0     | 0     | 0     |
| 22        | 0    | 0    | 0     | 0     | 0     | 0     | 0     | 0     | 0     | 0     | 0     | 0     | 0     | 0     | 0     | 0     | 0     | 0     | 0     | 0     | 0     | 0     | 0     | 0     |
| 23        | 0    | 0    | 0     | 0     | 0     | 0     | 0     | 0     | 0     | 0     | 0     | 0     | 0     | 0     | 0     | 0     | 0     | 0     | 0     | 0     | 0     | 0     | 0     | 0     |
| 24        | 0    | 0    | 0     | 0     | 0     | 0     | 0     | 0     | 0     | 0     | 0     | 0     | 0     | 0     | 0     | 0     | 0     | 0     | 0     | 0     | 0     | 0     | 0     | 0     |
| 25        | 0    | 0    | 0     | 0     | 0     | 0     | 0     | 0     | 0     | 0     | 0     | 0     | 0     | 0     | 0     | 0     | 0     | 0     | 0     | 0     | 0     | 0     | 0     | 0     |
| 26        | 0    | 0    | 0     | 0     | 0     | 0     | 0     | 0     | 0     | 0     | 0     | 0     | 0     | 0     | 0     | 0     | 0     | 0     | 0     | 0     | 0     | 0     | 0     | 0     |
| 27        | 0    | 0    | 0     | 0     | 0     | 0     | 0     | 0     | 0     | 0     | 0     | 0     | 0     | 0     | 0     | 0     | 0     | 0     | 0     | 0     | 0     | 0     | 0     | 0     |
| 28        | 0    | 0    | 0     | 0     | 0     | 0     | 0     | 0     | 0     | 0     | 0     | 0     | 0     | 0     | 0     | 0     | 0     | 0     | 0     | 0     | 0     | 0     | 0     | 0     |
| 29        | 0    | 0    | 0     | 0     | 0     | 0     | 0     | 0     | 0     | 0     | 0     | 0     | 0     | 0     | 0     | 0     | 0     | 0     | 0     | 0     | 0     | 0     | 0     | 0     |
| 30        | 0    | 0    | 0     | 0     | 0     | 0     | 0     | 0     | 0     | 0     | 0     | 0     | 0     | 0     | 0     | 0     | 0     | 0     | 0     | 0     | 0     | 0     | 0     | 0     |
| 31        | 0    | 0    | 0     | 0     | 0     | 0     | 0     | 0     | 0     | 0     | 0     | 0     | 0     | 0     | 0     | 0     | 0     | 0     | 0     | 0     | 0     | 0     | 0     | 0     |

Table 8.31. The matrix rows represent the semantically generalized product constrained to the 10 hectares MMU (Fig. 7.4); columns the semantically generalized product constrained to the 25 hectares MMU (Fig. 7.5). The principle diagonal shows how Pcor clusters have been emphasised/reduced by passing from the lower to the higher MMU.
8.13 Propagation of Error

In this section the errors derived from the procedures \textit{FindIntExtPoly()} and \textit{TempProc()} are estimated. These errors result in small sections of closed boundaries which have not been recognised by the two procedures and consequently have not been appropriately canceled during the merging activity (Fig. 6.15, Fig 6.16, and Fig. 6.17). This is due to two factors:

1. Occurrence of errors in the initial partitioning of the image, derived by the segmentation algorithm SED (section 4.3); and

2. Incomplete version of the set of templates (3x3 pixels windows) which may not cover the entire range of possibilities, including segmentation errors.

The existence of these small "undeleted" sections of boundaries in the merged products, causes the propagation of errors during the Thematic Smoothing. The smoothed products (Fig. 6.21 and Fig. 6.22) in fact present black regions within polygons where undeleted boundaries were found. Black regions had to be removed before testing the Semantic Generalization, and the smoothed product shown in Fig. 6.21 has been chosen for the manual correction since it presents less error. The manual correction has been performed pixel-by-pixel comparing the original classified image in order to simulate the Smoothing algorithm.

The confusion matrix generated cross tabulating the original smoothed product with the corrected product (Fig. 6.23) is shown in Table 8.32. The matrix rows show the information related to the corrected image and columns the original smoothed product. As already introduced in section 8.1, the products generated by the generalization process, as deriving from the segmented image, present an image-border formed by pixels set to 0 value. While the closed boundaries are formed by pixels set to 255 value.

The principle diagonal of the matrix represents the occurrence of each image-class, border and boundaries which have been appropriately preserved during the manual correction of black regions. The total of these occurrences is calculated to be 62172 pixels which corresponds to 95\% of the entire image size (65536 pixels).

Everything which is not on the principle diagonal is error, which is of two types:

A. The error propagated by the combination of initial errors in the segmentation with the performance of the procedures \textit{FindIntExtPoly()} and \textit{TempProc()}; and

B. The error introduced by manual correction.
Error A, black regions within polygons, is represented in the first column, from left) of the matrix excluding the first entry which belongs to the principle diagonal. In fact 833 black pixels have been manually associated with the image-class “Soil”, 1126 black pixels with the image-class “Grass”, 64 black pixels with the image-class “Cereals” etc. The total of these occurrences is calculated to be 2713 pixels, which corresponds to 4% of the entire image (65536 pixels).

Error B, misclassified pixels, is represented in all the entries of the matrix which do not lie on the principle diagonal and do not belong to the first column. Thus from left to right, 72 boundary pixels have been associated with border pixels (row 1, column 2), 141 boundary pixels have been associated with the image-class “Soil” (row 3, column 2), 1 “Grass” pixel has been associated with the image-class “Forest” (row 7, column 4), 162 “Urban” pixels have been associated with the image-class “Soil” (row 3, column 8) etc. The total of these entries is calculated to be 651 pixels, which corresponds to 1% of the entire image (65536 pixels).

From the confusion matrix shown in this section, the number of pixels associated with the “border” and the “boundaries” introduced in section 8.1 may be derived. In fact, in the corrected smoothed product, used to test the Semantic Generalization, 1321 “border” pixels are calculated, as the sum of the entries: row 1, column 1 (1249 pixels) and row 1, column 2 (72 pixels), and 9667 “boundary” pixels are calculated, as shown in the entry: row 2, column 2. The individual error for the two categories of pixels (border and boundaries) is 0.1% (corresponding with the 72 misclassified pixels). However, all together the “background” pixels as used in the estimations of this chapter present no error.

Considering that the two procedures FindIntExtPoly() and TempProc() and the entire Generalization process are working prototypes, which have been applied to “uncertain” input boundaries information, the Geometric Generalization worked correctly for 96% of the entire image (65536 pixels) which is an highly satisfying and promising result.
Table 8.32. The matrix rows represent the corrected geometrically generalized product (Fig. 6.23); columns the original geometrically generalized product (Fig. 6.21). The principle diagonal represent the success of the Geometric Generalization which is 96%.
CHAPTER 9
CONCLUSIONS

The ability for an automatic digital generalization process to derive a cartographic representation of land cover satellite-derived information has been proved in this research. The automatic digital generalization process developed for this thesis uses only satellite-derived information, transformed to a land cover classified image, segmentation image and associated non-image information are obtained independently from the same original Landsat TM image. The generalized product is compatible, spatially and thematically, with CORINE land use digital maps.

It has also been shown in this thesis that the analysis of the available data in a per-object fashion is suitable for a conversion of data which is automatic and consistent with the spatial and thematic characteristics of the classified image. Further, the organisation of the generalization process in a step-wise and rule-based fashion has been shown to be an appropriate strategy for the automatic and contemporary control, verification and management of spatial, thematic and statistical conditions.

For this type of process the a-priori definition of a computational model supporting the automation and maintaining the consistency of application of the process is necessary. For this purpose, the following conclusions have been reached. The computational model supporting the digital generalization process involves several aspects.

1) The definition of a model of spatial entity (the image-object) which is essential to unite all the spatial, thematic and statistical characteristics of the image from a per-image to a per-object representation of the original information.

2) The organisation of the available information in terms of:
   - general characteristics, the list of land cover types (the classification scheme);
   - spatial characteristics, the list of independent image-objects in the image, their geometrical description, the description of their spatial relationship of adjacency and the quantification of the adjacency between each pair of image-objects in terms of length and strength;
Conclusions

- **per-object contextual characteristics**, the list of thematic characteristics of each image-object; and
- **statistical characteristics** (image-statistics), the percentages of occurrence of land cover classes in the image overall and per-object.

3) The definition of a **model of activity** essential to describe the:
   - type of generalization activity;
   - input conditions (spatial, contextual and statistics);
   - expected conditions (after the activity); and
   - list of sub-activities and conditions for activation.

4) The organisation of **production rules** (IF-THEN-ELSE) which are a simple and appropriate tool to support an objective and intelligent generalization activity.

In this thesis an intelligent method for automatic and unsupervised exploitation of land cover satellite-derived information in deriving spatial information suitable for GIS input has been presented. The digital generalization process developed for this research analyses land cover information in a **per-object** fashion consistent to the image overall and to the per-object context. The result is a final product, which still preserves the original characteristics while representing information at a higher level of abstraction in a cartographically acceptable form.

In this thesis a full and automatic integration of data has also been presented, which combines the available data and derives a separate set of per-object information in both image and non-image format. The integrated information represent the set of knowledge used by the generalization process. Different types of knowledge (spectral, spatial and contextual) are automatically combined by the process while generalizing (under the guidance of the computational model), to automatically extract and organise the necessary knowledge for each generalization activity.

The needs summarised by Barr and Barnsley (1995) and listed in chapter 2 of this thesis concerning the attempt to adapt the methods of photo-interpretation to the analysis of satellite images have all been satisfied in the processing chain for automatic generalization developed for this research. Proof has been given of the availability for an automatic simulation of the objective component of the cartographer’s knowledge, which may be objectively translated in a computational model. Of course, the subjective “human” reasoning which is a combination of intuition, imagination and practical experience, may not be mathematically described in a
computing algorithm because they are expert-dependent, experience-dependent and scenario-dependent, which are conditions not generally applicable. These limits of the subjective knowledge logically should not be involved in a generally applicable process. The generalization activities developed for this research are simple, fully automatic and generally applicable; they are independent from the original land cover information and independent from the user (experienced or inexperienced).

In this thesis, three main activities have been identified as essential for a consistent digital generalization process, which uses only satellite-derived information. However, the processing chain may accept other, and different, spatial information. The generalization activities are applied in sequence and in the following order:

- Spatial Generalization;
- Thematic Smoothing; and
- Semantic Generalization.

The sequence of the three activities allows the process to work consistently with basic cartographic principles (chapter 2), reducing the unnecessary detail and enhancing the important information (*principle of simplification*), ordering and grouping similar data into categories (*principle of classification*) and logically extending the information contained in the classified image (*principle of induction*).

The methodology of cartographers in selecting the entities to be portrayed in the final map and in selecting the appropriate operator to apply has been modelled and simulated in an automatic and rule-based mechanism. This mechanism uses spatial and contextual constraints which are easy to control and are generally applicable, and allows the automatic extraction of the necessary knowledge from the available data to evaluate the constraints (Spatial Generalization and Thematic Smoothing). The cartographer's knowledge has been modelled in an expert system which evaluates the information to convert, based on an *hypothesis verification* mechanism of reasoning, involving quantitative and qualitative characteristics of the available data (Semantic Generalization).

The result of the generalization activity is a raster product representing land use information, provided with non-image information describing the independent image-objects in all their intrinsic and external characteristics. This allows direct reference to ground co-
Conclusions

ordinates. The generalized product is thus suitable for entry, as is, in a GIS database. In the particular case of this thesis, the product is compatible with CORINE digital maps.

The generalization process developed for this thesis, and the results obtained (chapter 8) reinforce and facilitate the complementary relationship between remote sensing and GIS technologies. It represents the "bridge" for linking together these two distinct but complementary disciplines. The technical problems outlined in chapter 2 for operational integration of GIS/remote sensing data have been overcome by the digital generalization process. In fact positional and categorical errors may be automatically recognised and corrected by using the supervised and intelligent process, which analyses independent spatial entities in their respective context, as described in chapter 6 of this thesis. It has also been proved that an image of pixels may be analysed in terms of image-objects thus preserving the overall image characteristics while simplifying the image context by generalizing independently each image-object. This emphasises the concept that the "pixels-versus-polygons" dilemma is only a matter of spatial representation. Further, the "raster-to-vector" dichotomy (chapter 2) does not represent a problem for using the final product of the digital generalization process because it may be decomposed and each image-object (geometrically described by the process in a per-edge description) may be directly represented, edge-by-edge, in vector format or each image-object may be independently processed by GIS activities in raster format, or directly compared with geographic co-ordinates etc.

One of the technical problems highlighted in chapter 2 for operational GIS/remote sensing data integration was the "error propagation". For both image processing and manual map production there is a "variable" margin of error introduced during the automated or manual elaboration of original data. In this thesis, the assumption that the classified image was not introducing errors in the distribution of themes has not limited the performance of the generalization process. On the contrary, the results obtained (as described in chapter 8) have shown the general correctness of the original land cover information. Although the risk of error in both classified images and manually produced maps is present, it has been clearly demonstrated that the general characteristics of the land scenario always match in the two different graphic representations. In fact if a river exists in the study area it will certainly be preserved in shape and location. Differences might occur in the information about fine detail, for example the exact location of the river edges. This, as seen in chapter 6 of this thesis, may
generate positional and attribute errors, which may be automatically and objectively eliminated. The spatial and thematic simplification of the available land cover information manipulates the fine detail information which if not strongly related to the image context does not survive the generalization activities. Thus, the original fine detail differences between input image and target map do not, for the majority of cases, survive in the final product. One must remember that both generalized product and target map represent “general” information.

The digital generalization, as described in this thesis, naturally allows the enhancement of “matching” information while naturally deleting the detail. It may then be concluded that the propagation of error during both image processing and manual map production may be reconsidered as “a source of error” but not as technical impediment for integrating GIS and remote sensing data. This “source of error” may then be reduced by the every-day more sophisticated computing technologies.

The limits outlined by Unwin (1986) (chapter 2) in spatial analysis, which are the irreversible destruction of information while selecting and enhancing other selected information from the original input during manual data manipulation, and the lack of geographical precision in the majority of maps have been overcome by the digital generalization process presented in this thesis. In fact, the initial “objective” extraction of image-objects based on computational and generally applicable constraints (such as the gradient magnitude of pixels referred to during edge detection) and the consequent per-object analysis of low-level information based on the evaluation of per-object and overall image-statistics and context make the simplification free from “subjective” human interpretation, make the overall simplification process repeatable. Further, the use of satellite-derived information during digital generalization allows direct reference to ground co-ordinates, making the final generalized product appropriate for accurate spatial location in a GIS environment and at the same time making compatible GIS and Cartographic information.

The results obtained from the performance of the automatic digital generalization process, discussed in chapter 8, are highly promising. A fully automatic, intelligent and unsupervised processing chain which:

- Elaborates satellite-derived land cover information;
- Simplifies the geometry and the content of the input information using only satellite-derived information;
• Brings the input information to a higher level of abstraction;
• Converts the land cover nomenclature into the land use nomenclature compatible with CORINE maps; and
• Generates products satisfying cartographic principles while still spatially and thematically consistent to the original low-level information.

Furthermore, this chain has been implemented in a working prototype, and has opened new frontiers for the operational integration of the Cartography, GIS and Remote Sensing communities.
FURTHER WORK

From the experience acquired in the process of this research and from the results obtained by the digital generalization process presented in this thesis, further work is outlined:

1. The initial partitioning of the satellite image in closed boundaries represents the major limit of the generalization processing chain. A 100% correct product from a segmentation algorithm is very rare. Interesting research in this field would be the development of a second version of the process *PolygonEdgeDescription()* (chapter 5 of this thesis) responsible for the verification of closed boundaries.

2. The two procedures *FindIntExtPoly()* and *TempProc()* (chapter 5, chapter 8) of the automatic digital generalization process, which are working prototypes might be revised in a specific and dedicated study for completion.

3. Multi-temporal image analysis have been used with success for crop type distinction as reported in chapter 2, however, in this research one single-date classified image has been used to provide information to the generalization processing chain. The reason for this was that the access to one single image was foreseen for this project. It was not possible to access imagery of other areas because it was not part of this specific project. The logical and consequent suggestion is the introduction of multi-temporal information to submit to the Geometric and Semantic generalization procedures during the image conversion. Information concerning crop types, phenological calendars (phases) and calendars of the agriculture practices specific for the area of interest, if available, reliable and updated, might be used by the expert system in the analysis of several multi-date classified images.

4. Further verification of the automatic generalization process is required before it may be generally applied. This could take the form of analysis of different geographical areas including different cover types.

5. Since the methods developed here include both geometric and semantic elements they could be applied to other class areas maps such as soil and geological maps. The final suggestion is therefore that experiments with other data types would be appropriate.
PUBLICATIONS

The list of publications prepared and presented to conferences, seminars and courses during the period devoted to this research is given below:

1. S. Goffredo, 1992: “Sviluppo di un ambiente interattivo per una elaborazione intelligente delle immagini”. Tesi di Laurea - Universita’ degli Studi di Milano - (Italy) - Corso di Laurea in Scienze dell’Informazione


7. S. Goffredo, 1995: “Knowledge-Based Automatic Generalization for Satellite-Derived Thematic Products”. Winner proposal of one GISDATA fellowship to participate to the ESF-GISDATA and NSF-NCGIA 1995 Summer Institute in Geographic Information sponsored by the European Science Foundation at the University of Southern Maine, Freeport, Maine, USA


APPENDIX A

Characteristics:
- Spatial Controls performed on the variable `in_out` of the structure `_poly_info{}`
- Pixel Neighbourhood 3x3
- Intersection = central pixel P(x, y)

Neighbourhood Conditions to be satisfied by the intersection on the closed boundary:
(reminder: a pixel set to 1 is a boundary pixel, a pixel set to 0 is not)

\[
\begin{align*}
\text{cond 1: } & p(x - 1, y - 1) = 0 & \text{cond 9: } & p(x - 1, y - 1) = 1 \\
\text{cond 2: } & p(x , y - 1) = 0 & \text{cond 10: } & p(x , y - 1) = 1 \\
\text{cond 3: } & p(x+1 , y - 1) = 0 & \text{cond 11: } & p(x+1 , y - 1) = 1 \\
\text{cond 4: } & p(x - 1, y ) = 0 & \text{cond 12: } & p(x - 1, y ) = 1 \\
\text{cond 5: } & p(x+1 , y ) = 0 & \text{cond 13: } & p(x+1 , y ) = 1 \\
\text{cond 6: } & p(x - 1, y+1) = 0 & \text{cond 14: } & p(x - 1, y+1) = 1 \\
\text{cond 7: } & p(x , y+1) = 0 & \text{cond 15: } & p(x , y+1) = 1 \\
\text{cond 8: } & p(x+1 , y+1) = 0 & \text{cond 16: } & p(x+1 , y+1) = 1 \\
\end{align*}
\]

Spatial Description of Neighbourhood Conditions (blank pixels correspond to pixels set to 0):

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<th></th>
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<th>CONDITIO NS = 9, 10, 11</th>
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</thead>
<tbody>
<tr>
<td>I</td>
<td>I</td>
<td>controls on <code>_poly_map</code> variable</td>
</tr>
<tr>
<td>I</td>
<td></td>
<td>TYPE 2 = START</td>
</tr>
</tbody>
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<table>
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<th></th>
<th>CONDI TIO NS = 3, 9, 10</th>
</tr>
</thead>
<tbody>
<tr>
<td>I</td>
<td>I</td>
<td>TYPE 1 = END</td>
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<tbody>
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<td>I</td>
<td>controls on <code>_poly_map</code> variable</td>
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<tr>
<td>I</td>
<td></td>
<td>TYPE 4 = START</td>
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<table>
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<tr>
<th></th>
<th></th>
<th>CONDI TIO NS = 1, 10, 11</th>
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</thead>
<tbody>
<tr>
<td>I</td>
<td>I</td>
<td>TYPE 3 = END</td>
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<table>
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<tbody>
<tr>
<td>I</td>
<td>I</td>
<td>TYPE 6 = START</td>
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</tbody>
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<tr>
<th></th>
<th></th>
<th>CONDITIO NS = 10, 11, 13</th>
</tr>
</thead>
<tbody>
<tr>
<td>I</td>
<td>I</td>
<td>TYPE 5 = END</td>
</tr>
</tbody>
</table>
Appendix A

CONDITIONS = 1, 10, 11, 14
controls on filled variable
TYPE 40 = START

CONDITIONS = 3, 9, 10, 14
TYPE 39 = END

CONDITIONS = 1, 2, 11, 14
TYPE 42 = START

CONDITIONS = 9, 10, 11, 14
controls on poly_map variable
TYPE 41 = END

CONDITIONS = 1, 2, 3, 13, 14
TYPE 44 = START

CONDITIONS = 9, 10, 11, 13, 14
TYPE 43 = END

CONDITIONS = 1, 10, 11, 12
TYPE 46 = START

CONDITIONS = 3, 9, 10, 12
TYPE 45 = END

CONDITIONS = 1, 2, 11, 12
TYPE 48 = START

CONDITIONS = 9, 10, 11, 12
TYPE 47 = END

CONDITIONS = 1, 2, 3, 12, 13
TYPE 50 = START

CONDITIONS = 9, 10, 11, 12, 13
TYPE 49 = END

CONDITIONS = 9, 10, 11
controls on poly_map variable
TYPE 53 = END

CONDITIONS = 2, 9, 11
TYPE 54 = END

CONDITIONS = 9, 10, 11, 13
TYPE 55 = START

CONDITIONS = 2, 3, 9, 13
TYPE 56 = END
Intersection types 21, 22, 53 and 54 are special combinations of boundary pixels which may represent 1) a top or a bottom end of a very thin boundary or 2) the first or the last pixel in a sequence of intermediate intersections. Those intersections are set to and END segment by convention, because in no case they may represent a START segment.

Intersection types 51, 52, 57, 58 and 59 do not exist anymore in the source code, and a new new numerical ordering of the types numbers might be confusing at this stage of analysis.

Intersection types 63, 64, 65 and 66 are templates involving more than two neighbours in the template and need contemporary controls in variables .in_out, .filled and .poly_map.
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