ADVANCES IN KNOWLEDGE BASED SIGNAL PROCESSING:  
A CASE STUDY IN EMG DECOMPOSITION

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

by

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May 1991
The conquests of future tomorrows
lie in the soul and imagination of man........
Declaration of Originality

A thesis submitted in fulfilment of the requirements for the degree of Doctor of Philosophy in the Department of Engineering, The University of Leicester, U.K. All work recorded in this thesis is original unless otherwise acknowledged in the text or by references. No part of it has been submitted for any other degree, either to the University of Leicester or to any other University.

Gareth Loudon
May 1991
Acknowledgements

Many people have helped me during my three years of research including my family, friends and colleagues. I would like to thank them all for their help and support.

Particular thanks go to Professor Barrie Jones who took me on as a research student in 1988, provided financial support for my research and supervised my study. His enthusiasm, advice and help during the three years have made the time spent at Leicester thoroughly enjoyable as well as extremely beneficial.

I would also like to thank Dr. Arvindra Sehmi for the enormous amounts of time and effort he has spent helping me during my research, Mrs Alison Charles for her kindness and help, Dr. John Fothergill for his contribution to the research group as a whole and all the members of the research group at Leicester (including Salih, Dave, Lin, Wang, Andy, Assad, Naim, Zainol, Silvio, Tuan, Jim, Lee, Pih Lung and George). I must also thank Dr. Brezinova and Dr. Ponsford at Leicester Royal Infirmary for their help in explaining the complex problems that exist in electromyography and for analysing EMG signals for me. Thanks also go to Medelec Ltd. and SERC for their financial support.

A very special thank you is reserved for my family who have encouraged and supported me through all my ups and downs and who have believed in me.

I would also like to take this opportunity to thank two special friends, Mr. Basil William Greenwood and Mr. Christopher Ryan, who have made my stay at Leicester about as enjoyable as watching England play cricket.

Finally I would like to thank the most important person of all - Ms. Harsangeet Kaur Bhullar.
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Abstract

This thesis relates to the use of knowledge-based signal processing techniques in the decomposition of EMG signals. The aim of the research is to fully decompose EMG signals recorded at fairly high force levels (up to twenty percent maximum voluntary contraction) automatically into their constituent motor unit potentials to provide a fast and accurate analysis routine for the clinician. This requires the classification of non-overlapping motor unit action potentials (MUAPs) and superimposed waveforms formed from overlapping MUAPs in the signal.

Firstly, digital filtering algorithms are used to reduce noise in the signal. A normalisation and compression of the filtered signal is then performed to reduce the time of the analysis. Non-overlapping MUAPs are classified using a statistical pattern recognition method. The method first describes the MUAPs by a set of features and then uses diagonal factor analysis to form uncorrelated factors from these features. An adaptive clustering technique groups together MUAPs from the same MU using the uncorrelated factors. The decomposition of superimposed waveforms is divided into two sections. The first section is a procedural method that finds a reduced set of all possible combinations of MUAPs which are capable of forming each superimposed waveform. The second section is a knowledge-based analysis of the selected MUAP combinations forming each superimposed waveform. An expert system has been designed to decide which combination is the most probable by studying the motor unit firing statistics and performs uncertainty reasoning based on fuzzy set theory.

The decomposition method was tested on real and simulated EMG data recorded at different levels of maximum voluntary contraction. The different EMG signals contained up to six motor units (MUs). The new decomposition program decomposed all MUAPs in the EMG signals tested into their constituent MUs with an accuracy always greater than ninety-five percent. The decomposition program takes about fifteen seconds to classify all non-overlapping MUAPs in an EMG signal of length one second and on average, an extra nine seconds to classify every superimposed waveform. Hardware limitations did not enable the testing of EMG signals containing more than six MUs. The results also show that the computer analysis can simulate the reasoning of a human expert when studying a complex EMG signal.
GLOSSARY OF TERMS

| AcS | Active Segment |
| CRDFT | Canonically Registered Discrete Fourier Transform |
| CF | Certainty Factor |
| DEMGES | Decomposition of EMG Expert System |
| DENDRAL | A program for generating explanatory hypotheses in organic chemistry |
| DFD | Data Flow Diagram |
| DFT | Discrete Fourier Transform |
| DSP | Digital Signal Processor |
| ED | Euclidean Distance |
| EEG | Electroencephalogram |
| EMG | Electromyographic or myoelectric signal |
| FM | Frequency Modulated |
| MA | Minimum Activity |
| MFP | Mean Firing Period |
| MU | Motor Unit |
| MUAP | Motor Unit Action Potential |
| MUAPT | Motor Unit Action Potential Train |
| MVC | Maximum Voluntary Contraction |
| MYCIN | A computer system for diagnosing infectious diseases |
| NCV | Nerve Conduction Velocity |
| ND | Network Distance |
| PROSPECTOR | An expert system for use in mineral exploration |
| r | Pearson’s product moment correlation coefficient |
| SD | Standard Deviation |
| SEP | Somatosensory Evoked Potential |
| SERC | Science and Engineering Research Council |
SFP ................................................. Smallest Firing Period
SNR ................................................ Signal to Noise Ratio
TA .................................................... Total Area
TP .................................................... Turning Point
TV .................................................... Threshold Value
VL .................................................... Vector Length
XCON ............................................. eXpert CONfigurer
CHAPTER 1  The origin and analysis of the EMG signal

1.1 Introduction

Electromyography is the study of electrical (EMG) signals recorded from a muscle during a forceful contraction. The electrical signals result from the neuromuscular activation associated with a contracting muscle. Diseases to nerves and muscles result in changes to the characteristics of the electrical signal recorded. An analysis of the electrical signals would therefore be of great benefit to the diagnosis of neuromuscular disorders. This chapter firstly gives a brief background to the field of electromyography. The chapter then highlights the important information contained in the electrical signals and some of the problems associated with extracting the information for the doctor to study. Finally the chapter gives a review of some past EMG analysis methods.

1.2 Background to Electromyography

Each muscle contains groups of many muscle fibres. These muscle fibres are cylindrical in shape and vary in length and width (9 to 40mm and 50 to 100um respectively). A group of muscle fibres is connected to a nerve fibre as shown in Fig.[1.1]. Each group of muscle fibres and the nerve fibre connecting it are known as a motor unit (MU).

Muscle fibres are activated by impulses sent down motor nerves from the spinal cord. Each nerve impulse innervates a group of muscle fibres. As the impulse is received by the muscle fibres, the permeability of muscle fibre membrane is changed and it becomes temporarily depolarised. This depolarisation passes to adjacent regions of the membrane so that a wave of electrical potential, the so-called action potential, propagates along each muscle fibre. This may be detected using various types of electrodes and the observed waveform is known as the motor unit action potential (MUAP). Examples of simulated MUAPs are given in Fig.[1.2].
Fig. [1.1]. A schematic diagram of a motor unit.
Fig.[1.2]. Examples of simulated motor unit action potentials.
Normal human muscles display mainly bi and triphasic MUAPs with less than ten percent of MUAPs being polyphasic in shape. During old age the percentage of polyphasic MUAPs and MUAP durations increases. The amplitude and shape of an observed MUAP are a function of the geometrical properties of the motor unit, muscle tissue, and detection electrode properties. In order to sustain a muscular contraction, continual impulses need to be sent by the nervous system to the muscle fibres to produce a train of motor unit action potentials (MUAPT). A single MUAPT is observed when the fibres of only one motor unit in the vicinity of the electrode are active. Such a situation occurs only during a very weak muscle contraction. Fig.[1.3] shows an EMG signal containing a single motor unit action potential train recorded with a concentric needle electrode.

As the force output of a muscle increases, motor units having fibres in the vicinity of the electrode become activated and several MUAPTs are detected simultaneously. The summation of these individual MUAPTs from all active motor units within the pickup area, gives rise to a measurable voltage. This is called the myoelectric or EMG signal (Basmajian and DeLuca, 1985). At a constant force level the intervals between MUAPs in a MU are fairly constant. The distribution of the intervals is a close approximation to a gaussian distribution (Andreassen and Rosenfalck, 1980).
1.3 Neuromuscular diseases

There are two main types of disease that can occur in the neuromuscular system - myopathic diseases and neuropathic diseases.

1.3.1 Myopathic diseases

A myopathic disease describes primary muscle damage. The diagnosis of many myopathies is based on the study of the EMG signal. A myopathic EMG signal will contain some spontaneous activity such as fibrillation potentials and positive sharp waves. The MUAPs recorded are usually shortened in duration, their amplitudes are small and the percentage of polyphasic potentials is increased. The EMG signal is full in spite of reduced strength at maximum voluntary contraction (MVC). In general, the motor and sensory conduction velocities are normal.

The firing rates of the MUs are generally higher than normal, possibly to compensate for the degenerating muscle fibres (Ludin, 1980). The shortened duration and reduced amplitude of the myopathic MUAPs are due to the degeneration of some muscle fibres. The polyphasic shape is thought to be caused by a combination of a reduced number of action potentials forming the MUAP and the increase in jitter. Jitter is the variability in excitation of each muscle fibre due to the random discharge of acetylcholine packets released at each neuromuscular junction (Basmajian and DeLuca, 1985). Jitter measurements can be made using two muscle fibres innervated by the same nerve fibre (axon), where the action potential of one muscle fibre is used as a reference. When motor units are voluntarily activated the jitter is the difference in conduction times of impulses sent from the nerve to the muscle fibre recording site. In certain stages of a myopathic disease changes along the degenerating muscle fibre could lead to irregularities in impulse propagation before transmission completely fails and thereby increasing jitter. A second reason why jitter might increase could be due to disturbed motor end plate function (Stalberg and Trontelj, 1979).

1.3.2 Neuropathic diseases

A neuropathic disease describes damage to the nerve fibres. There are three types of pathology that can occur in a neuropathic disease:-
1) Neurapraxia: This is when there is a temporary dysfunction of the nerve. There is no major change in the nerve structure.

2) Demyelination: This is when there is damage to the myelin sheath that covers the nerve fibre (see Fig.[1.1]). There is a slowing in nerve conduction velocity (NCV). The NCV is normally less than half of the expected value. The second potential sometimes recorded in NCV tests (known as the F wave) is polyphasic in shape. The F wave amplitude is also reduced and the duration increased. The F wave is formed from the impulse travelling proximally along the nerve for a certain distance before travelling distally to activate the muscle.

3) Axonal Lesion: This is when some nerve fibres are cut or damaged. There is no conduction down the cut fibres. The F wave is small in amplitude and there is no polyphasic shape. The NCV is normal/reduced (Lenman and Ritchie, 1977).

The neuropathic disorder can be sensory, motor or a combination of the two. A sensory neuropathy occurs when the nerve fibres connected to the skin surface are damaged. In this case the EMG signals of all the muscles will be normal, and only the sensory nerve conduction velocity tests will be abnormal. A motor neuropathy occurs when the nerve fibres connected to muscles are affected. In this case the EMG signal and motor NCV tests will be abnormal.

A neuropathic EMG signal will contain spontaneous activity such as fibrillation potentials and positive sharp waves, even at rest. The MUAPs recorded are usually longer in duration than normal, they have larger amplitudes and the percentage of polyphasic potentials is increased. The activity of the EMG signal is reduced at maximum voluntary contraction (MVC).

The firing rates of the MUs are generally slightly higher than normal. There is an increased variability in the firing periods of the MUs (Dorfman et al., 1989). The MUAP shape changes are largely due to the incorporation of denervated muscle fibres into surviving motor units which become larger. As a result the spatial distribution of the muscle fibres in a motor unit increases. The reinervated muscle fibres are connected by very thin nerve endings which are poorly myelinated and cause slower conduction. The large amplitude of the neuropathic MUAP is therefore due to the
increased number of muscle fibres per motor unit. The increased MUAP duration and increased percentage of polyphasic MUAPs is due to the larger spatial distribution of muscle fibres (Ludin, 1980).

1.4 Analysis of the EMG signal

An example of an EMG signal recorded from the adductor pollicis muscle in the arm using a surface electrode is shown in Fig.[1.4]. The recording was made during a test where the subject maintained a force level at fifty percent of his maximum voluntary contraction. The test was carried out under isometric conditions. The problem of extracting information on the MUAPs contained in such a signal is not a trivial one. The EMG signal contains noise at a low frequency due to movement of the electrode relative to the active muscle fibres, and also at higher frequencies due to other electrical activity in the environment. Electrode movement is exaggerated when the doctor has to adjust the settings on the recording equipment while trying to keep the electrode still. Other background activity in the EMG signal is caused by MUAPs that are at a far distance from the recording electrode. They are smaller in amplitude and smoother in shape in comparison with MUAPs near to the recording electrode which can be detected with relative ease.

Tests performed on different subjects result in EMG signals of varying amplitude being recorded. For a doctor to extract the MUAP data from the EMG signal by a visual analysis, he/she must manually set a triggering level. The triggering level separates background activity from the MUAP activity in the EMG signal. When a patient performs a muscular contraction at a fairly high force level it is difficult to identify all the MUAPs of any particular MUAP train, due to the high degree of overlap between MUAPs of different MU trains. Therefore, a doctor has to perform his/her visual analysis with EMG signals recorded at low force level tests. This means that only a small number of MUs can be captured in each test and therefore a large number of tests are required. Performing many tests at low force levels causes problems for the doctor. The repeating of tests means re-inserting the needle electrode into the muscle. This is painful for the patient and quite often restricts the number of tests that can be performed (hence reducing the reliability of the results). Another
Fig. [1.4]. An EMG signal recorded at 50% MVC.
problem is that some muscle fibres are only activated at higher force levels and therefore cannot be studied for the existence of neuromuscular diseases. A true representation of the muscle state may not be ascertained.

These problems faced in a clinical environment have led researchers to study ways of extracting MUAP information from an EMG signal with the aid of computer analysis routines. First attempts were to automatically extract MUAP information from an EMG signal recorded at very weak contraction levels of a muscle containing only one MUAPT. Research work was then undertaken to see if computer analysis programs could be written to extract all MUAP information from an EMG signal recorded at higher contraction levels containing many active MUs. The total success of the research work is still open to question. The next section describes three automatic detection schemes that have been designed to tackle the problem of MUAP extraction from an EMG signal.

1.5 Past methods for the decomposition of EMG signals

1.5.1 Introduction

The first method is by LeFever and DeLuca. It achieves the goal of decomposing an EMG signal into its constituent MUAP trains even when the EMG signal is recorded at maximum voluntary contraction (MVC). This is done at the expense of computational time and full automation. The second is a method by Gerber and Studer which decomposes an EMG signal at lower percentages of MVC using a fully automatic system. The third method is by McGill et al.. It attempts a fast automatic decomposition of an EMG signal at medium percentages of MVC, at the expense of not decomposing overlapping MUAPs. The following descriptions of the methods are derived from LeFever and DeLuca (1982), Gerber and Studer (1984) and McGill et al. (1985).

1.5.2 LeFever and DeLuca

LeFever and DeLuca record three channels of EMG data using a special bipolar needle electrode. This technique has the advantage of having high quality recordings from different areas within the muscle. The disadvantage is that it is not an electrode
commonly used in clinical practice. LeFever and DeLuca use a high pass filter with a cut-off frequency of 1kHz rather than at a lower frequency of 20Hz, so that the MUAP waveforms detected are of shorter duration. The filter setting also substantially reduces the amplitude of MUAP waveforms produced by muscle fibres more distant from the electrode because these MUAPs have slower rise times.

A sampling rate of 50kHz is used in the data acquisition since some of the MUAP waveforms obtained using the special electrode have frequency spectra up to 10kHz. The EMG signal is split into areas of activity and non-activity where only the segments of data containing positive or negative peaks above a preset triggering level are stored. The triggering level is selected by the operator depending upon the level of background noise in the data. The basic operation of the decomposition algorithm used by LeFever and DeLuca for the classification of non-overlapping MUAPs is described by the following four sequential steps.

1. **step 1**: The next MUAP waveform in the EMG signal is located.
2. **step 2**: It is determined if any of the previously detected MUs has produced this MUAP waveform. If not, it is classified as a waveform produced by a newly recruited MU.
3. **step 3**: This MUAP waveform and its time of occurrence are used to update the template and the firing statistics of the MU that has been detected. If this MUAP waveform is produced by a newly recruited MU, the MUAP waveform is used as the initial estimate of the MU template. Both the MU templates and firing statistics are used in the decision making process in the previous step (step 2).
4. **step 4**: This MUAP waveform is numerically subtracted from the EMG signal, and the whole process repeated. By subtracting the estimate of the MUAP waveform produced by the detected MU, MUAPs from other MUs (usually producing lower amplitude waveforms) with which it is superimposed may also be detected.

The method uses a template matching procedure and the firing statistics of the MUs. Superimposed waveforms containing overlapping MUAPs are decomposed in a similar manner. Only combinations of two waveforms, and thus two templates are
considered, since the computational time is prohibitive for more. The decomposition of a superimposed waveform is achieved by a template matching method, followed by a procedure which attempts to fit a second MUAP template to the residual waveform formed from the first stage. The method of LeFever and DeLuca achieves the decomposition of an EMG signal at one hundred percent of maximum voluntary contraction. The method enables the study of MU firing times at all force levels and how MUs are recruited and decimated. Three to eight MUs can be classified in an EMG signal using this method. It requires the assistance of a highly skilled operator to make decisions about information collected. The analysis takes five to thirty minutes to decompose an EMG signal (one second in length) containing eight MUs.

1.5.3 Gerber and Studer

Gerber and Studer record one channel of EMG data using a conventional needle electrode. A high-pass filter is used with a cut-off frequency of 32Hz to eliminate baseline drift and a low pass filter is used with a cut-off frequency of 3kHz for anti-aliasing. A sampling rate of 10kHz is used in the data acquisition.

The EMG is partitioned into active segments (AcSs) containing activity of the MUAPs, and inactive segments considered to contain only noise or background activity. The latter are disregarded. Each AcS is described by a feature vector \( f(x) \) which contains the following variables.

\[
\begin{align*}
Z_1 &= \max(x_{i+1} - x_i) \\
Z_2 &= \max(x_i - x_{i+1}) \\
Z_3 &= \max(x_i) - \min(x_i) \\
Z_4 &= \text{number of turns} \\
Z_5 &= \text{number of samples}
\end{align*}
\]

(1.1)

where \( x_i \) = magnitude of \( i^{\text{th}} \) element. The feature vector is then defined as:

\[
f(x) = \text{col}(x_1, \ldots, x_N, aZ_1, aZ_2, aZ_3, aZ_4, bZ_5)
\]

(1.2)

where \( a = 0.5N \) and \( b = 10 \) are weightings and \( N \) is the number of data points in each AcS. All the AcSs are clustered by a method known as the nearest neighbour method (Tryon and Bailey, 1970). The clustering method forms a binary tree whose nodes are the clusters and whose branches identify how the clusters are linked. The
nearest neighbour method can cluster MUAPs from the same MU that slowly change in shape from one occurrence to the next. The average waveform of each cluster group is used as a reference signal (MUAP template) in the next stage of the analysis where superimposed waveforms are decomposed.

The analysis first estimates the firing times of the MUAPs. These estimates are obtained independently of the templates for the MUAPs. Each superimposed waveform is then compared with the individual MUAP templates. The most probable MUAP constituents are selected by a template matching procedure. Only those choices whose approximation error and offset correction are below certain thresholds are accepted. The approximation errors between all possible combinations of templates (of two or threefold superpositions) and the superimposed waveform, are studied. The optimisation is started for the best approximation. This involves optimal estimation of the gains, delays and offsets. If the best approximation after the optimisation is acceptable, then this combination is considered to be true. Otherwise, the decomposition attempt is assumed to have failed. The decision is only made at the end, thus avoiding the decision for an acceptable solution before the best one has been checked and found.

The method by Gerber achieves the decomposition of an EMG signal at considerably high contraction levels. Seven MUs can be classified in an EMG signal using this method. Information is provided on the shape of the MUAPs, their variability in shape and the firing statistics of the MUs. The method is fully automatic, and does not require the aid of an operator.

1.5.4 McGill et al.

McGill et al. do not attempt the decomposition of superimposed waveforms, but concentrate on a fast implementation program. EMG data is recorded on one channel using a conventional needle electrode. A band-pass filter is used with cut-off frequency settings of 8Hz and 8kHz in conjunction with an anti-aliasing filter set at 5kHz. A sampling rate of 10kHz is used in the data acquisition. A digital filter known as a low pass differentiator is used to accentuate the MUAP spikes from the background activity. The method identifies the MUAPs in the EMG signal by performing template matching on the spikes in the filtered signal.
The method detects each spike that exceeds a set threshold and computes its canonically registered discrete fourier transform (CRDFT). The analysis is performed in the frequency domain to reduce the required sampling rate to 10kHz. *The spike's peak is located with high temporal resolution by interpolating the trigonometric polynomial specified by the DFT coefficients that approximates the continuous waveform underlying the samples.* Finally, the DFT is rotated (corresponding to time shifting) so that the peak is at the midpoint of the analysis interval.

Canonical registration implicitly aligns all the spikes and templates with one another in a peak to peak fashion. This alignment of the spikes with the templates is sufficiently accurate (since the spikes are so narrow) to allow the direct comparison between the two. The method performs template matching in the frequency domain to avoid the cost of transforming back into the time domain.

The method does not attempt to resolve superpositions and so fails to identify every firing of every MU. The filtered spikes are usually narrow enough to be identified at separations down to about 1ms, resulting in identification rates of between 40 and 70% in an EMG signal recorded at 30% of a person’s maximum voluntary contraction (MVC). After the spike trains have been identified, the method examines their firing patterns to verify that they correspond to valid MUAPs. The method identifies and merges together templates that correspond to the same MU. The identification is based on similarity of spike shape and regularity of the combined firing pattern of the templates.

The method identifies templates that are time locked to one another. These usually result from complex shaped MUAPs, including MUAPs with late components. This latter group produces multiple spikes when filtered, each of which is mistakenly identified as a separate unit. From each set of time locked templates, the method keeps only the one template with the most identified spikes.

The method by McGill et al. achieves the decomposition of an EMG signal up to thirty percent of maximum voluntary contraction. Fifteen MUs can be classified in an EMG signal using the method. The method can analyse a ten second EMG record in ninety seconds and is fully automatic.
1.5.5 Discussion

The method which LeFever and DeLuca use achieves the goal of decomposition at one hundred percent maximum voluntary contraction. This is slightly misleading because only a maximum of eight MUs can be classified during an analysis. This is similar to the number of MUs other researchers (like Gerber) can classify. Other drawbacks with the method are that:

- the decomposition takes a matter of hours to complete.
- a specially designed electrode recording three channels of data is used.
- a highly skilled operator is required to make decisions during the analysis.
- the MUAPs classified are highly filtered and provide limited diagnostic information for the doctor.

In future, the speed of computers will increase and reduce the analysis time but the requirement of a specially designed electrode, the need for a highly skilled operator and the distorted MUAP shapes that result will still be a problem.

Gerber attempts the decomposition of an EMG signal without distorting the MUAP shapes in the signal. The method for classifying non-overlapping MUAPs follows a very logical approach, although the time taken for computation is still too long for it to be feasible in a clinical environment. The method used for decomposing superimposed waveforms is also slow, requiring a great deal of computation to achieve its goals. It does not seem to be the most efficient solution.

McGill et al. can classify MUAPs in an EMG signal recorded at up to thirty percent of maximum voluntary contraction. McGill et al. use a conventional needle electrode and can extract up to fifteen MUs from an EMG signal. They concentrate on speed in their calculations and do not attempt to decompose overlapping MUAPs thus leaving a large percentage of MUAPs unclassified. Problems occur with the analysis when studying pathological MUAPs because of excessive configurational variability (McGill et al., 1985). The resultant MUAPs classified are also highly filtered because of the use of a low pass differentiator and therefore provide limited diagnostic information for the doctor.

The problem of decomposition is a balance between speed and complexity.
2.1 Introduction

A new approach to the decomposition of EMG signals has been undertaken, to overcome some of the problems arising in clinical EMG analysis and from previous EMG analysis methods. This chapter describes the framework of the design strategy used in the decomposition of EMG signals and an overview of the new decomposition method.

The new decomposition method attempts to decompose the EMG signal into its constituent MUAP trains under fairly high force level conditions (say 20% maximum voluntary contraction) using a knowledge based approach. The decomposition of an EMG signal at this force level would increase the number of MUAP trains recorded per test in comparison with clinical tests and therefore reduce the number of tests required for a conclusion to be formed. The reduction in the number of tests required and therefore a reduction in the number of times a needle electrode has to be re-inserted into a muscle has benefits for the doctor and patient. The patient is caused less discomfort by shorter examination times and the doctor can avoid situations where pain caused to the patient restricts the amount of EMG information available.

The new decomposition method is designed to produce accurate results in a dramatically reduced time period, in comparison with a visual analysis of the data. Problems such as high noise levels caused by a doctor manually setting a triggering level to extract MUAP information are reduced by the new method. The new work contains an expert system which attempts to simulate the reasoning processes of a human expert during the analysis of the data and therefore reduces the errors made in the decomposition. The expert system also explains the conclusions formed for the clinician to study.

Firstly, a description is given of the structured methods used in the software design of the new decomposition method. The different architectures of expert systems are then briefly explained with a section on how knowledge is acquired about a problem
domain for use in expert systems. Finally the main objectives of the work are
highlighted with an overview of the new decomposition method designed. The
description of the structured software design is derived from Pressman (1987). The
description of the expert system architecture is derived from Graham and Jones (1988)
and Merrit (1989).

2.2 Structured software design

Structured software design is divided up into three main sections: data design,
architectural design and procedural design. Data design focuses on the definition of
data structures, architectural design defines the relationships among major structural
elements of the program and procedural design transforms structural elements into a
procedural description of the software. Structured software design is a process through
which requirements are translated into a representation of software. Initially the
representation describes an overview of the software design. Subsequent refinement
leads to a design representation that is very close to source code. From a project
management point of view, structured software design is conducted in two steps.
Preliminary design is concerned with the transformation of requirements into data and
software architecture. Detail design focuses on refinements of the architectural
representation that lead to detailed data structure and algorithmic representations for
software. Some of the main criteria for a good design are that a design should:-

- exhibit a hierarchical organisation that makes intelligent use of control among
  the elements of software.
- be modular; that is, the software should be logically partitioned into elements
  that perform specific functions and subfunctions.
- contain a clear and separable representation of data and procedure.
- lead to modules (eg. subroutines or procedures) that exhibit independent
  functional characteristics.
- be derived using a repeatable method that is driven by information obtained
  during the software specification.

The software design should also be well documented explaining all the different
levels of complexity right down to the description of specific function actions.
2.2.1 Data design

Data design describes the data structures by logical representations identified during the software specification. The selection process normally involves a study of alternative data structures in order to determine the most efficient design or may simply involve the use of a set of modules that provide the desired operations upon some representation of an object. An important related activity during data design is to identify the program modules that must operate directly upon the logical data structures. The identification of these modules helps in determining which data structure representation to adopt.

2.2.2 Architectural design

Architectural design develops a modular program structure and represents the control relationships between modules of a program. A modular design means that a system is split up into different chunks or modules. Each module performs a specific task that is independent of other modules. In addition, architectural design defines interfaces, enabling data to flow throughout the program. A modular design reduces complexity, facilitates change and results in easier implementation by encouraging parallel development of different parts of a system. A modular design tries to follow three rules:

- **Functional independence:** functional independence is achieved by developing modules with a *single minded* function and an *aversion* to excessive interaction with other modules.

- **Cohesion:** a cohesive module performs a single task within a software procedure and requires little interaction with procedures being performed in other parts of a program.

- **Coupling:** Coupling is a measure of interconnection among modules in a program structure. Coupling depends on the interface complexity between modules. Software design strives for low coupling. Simple connectivity among modules results in software that is easier to understand and less prone to errors that propagate through a system.
2.2.3 Procedural design

Procedural design is carried out after the data and program structure have been described. Procedural design uses a set of logical constructs from which any program could be formed. The constructs are *sequence, condition and repetition*. Sequence implements processing steps essential in the specification of any algorithm, condition provides the facility for selected processing based on some logical occurrence, and repetition provides for looping. These three constructs are fundamental to structured programming.

The structured constructs were proposed to limit the procedural design of software to a small number of predictable operations. It has been shown by Edsger Dijkstra (1976) and others that the use of the structured constructs reduces program complexity and thereby enhances readability, testability and maintainability.

**Data flow diagrams** - A data flow diagram (DFD) is a graphical representation of the design. The technique describes the information flow through a program and the transforms that are applied as data move from input to output. DFDs are used to write the architectural and procedural design stages of the work. The basic form of a DFD is illustrated in Fig.[2.1]. The diagram is similar in form to other activity-flow diagrams proposed by Yourdon and Constantine (1978) for the design and analysis of programs. The data flow diagram is also known as a data flow graph or a bubble chart.

The DFD may be used to represent a system or software at any level of abstraction. The DFDs may be partitioned into levels that represent increasing information flow and functional detail. A level 01 DFD, also called a fundamental system model, represents the entire software element as a single bubble with input and output data indicated by incoming and outgoing arrows, respectively. Additional transforms and information flow paths are represented as the level 01 DFD is partitioned to lower level DFDs to reveal more detail.

DFD symbology is illustrated in Fig.[2.2]. A rectangle is used to represent an external entity. A circle or oval represents a process or transform that is applied to data and changes it in some way. An arrow represents one or more data items. All arrows on a data flow diagram should be labelled. The double line represents a data store (ie. stored information that is used by the software).
Fig. [2.1]. A data flow diagram (DFD).

- **External entity:** A source of system inputs, or sink of system outputs.
- **Process:** Performs some transformation of its input data to yield its output data.
- **Data flow:** Used to connect processes to each other, to sources or sinks; the arrowhead indicates direction of transfer.
- **Data store:** A repository of data, the arrowheads indicate net inputs and outputs to the store.

Fig. [2.2]. Data flow diagram symbology.
2.3 Expert systems

Expert systems are computer programs which encapsulate some human expertise for solving problems. An expert system contains four major system components. The interconnections between the major components are illustrated in Fig.[2.3].

![Diagram of an expert system]

**Fig.[2.3]. The structure of an expert system.**

The major components are:

- Knowledge base - a declarative representation of the expertise, sometimes described by IF THEN rules.
- Data base - the data which is specific to a particular problem that is being solved.
- Inference engine - the main controlling section of the expert system. The inference engine uses problem-specific data from the working storage and activates expertise in the knowledge base to solve a particular problem. The inference engine can contain goal driven reasoning (backward chaining) which uses IF THEN rules to repetitively break a goal into smaller sub-goals which are easier to prove, or data driven reasoning (forward chaining) which uses IF...
THEN rules to deduce a problem solution from initial data. The inference engine can also cope with uncertainty, which is the ability of the system to reason with rules and data which are not precisely known.

- User interface - the section that controls the information passing between the user and the system. The user interface also has the ability to explain the reasoning process that is used to reach a recommendation.

Many expert systems are built with standard products called expert system shells. The shell is a piece of software which contains the user interface, a format for declarative knowledge in the knowledge base, and an inference engine. Expert systems are also built with shells that are custom developed for particular applications.

The next seven sub-sections describe different aspects of an expert system. The first two sub-sections describe forms of knowledge and data representation. A brief description of reasoning strategies used in expert systems is then given, followed by an explanation of the problems caused by uncertain information. Finally, the interaction between the user and the expert system is discussed.

2.3.1 Production systems

Production systems represent knowledge in the knowledge base as IF..THEN constructions. The left hand side of a production rule of the form :-

IF A THEN B

is called its antecedent (or premise) and the right hand side its consequent (or conclusion). It may be interpreted in several ways. For example, the rules could be read as :- if a certain statement is true then another can be inferred or if a certain condition is satisfied then a certain action is suitable. The premise and the conclusion can be complex statements formed from simpler statements using the connectives AND and OR and the NOT operator. It is usually the case that only the premise contains these complex statements and the conclusion is a simple statement. A typical production would look like the one below.

IF (person is female AND person is mother) OR (person is male AND person is father) THEN person is parent.
Production systems combine rules as if there were an OR between the rules; that is between the premises of rules with the same conclusion. Each production rule describes a small independent area of knowledge and can therefore be added or subtracted from the knowledge base easily. This is one of the reasons why production rules have been used in the knowledge bases of many large scale expert systems. Another reason is that people can understand the concept of rules being used to describe knowledge. Three expert systems that use production rules in their knowledge bases are DENDRAL (Buchanan et al., 1969), MYCIN (Shortliffe, 1976) and PROSPECTOR (Duda et al., 1976). Production rules also form the basis of nearly all expert system shells. The production rules support a declarative style of programming because they are, in theory, independent from each other which considerably reduces maintenance problems. However, situations can occur where contradictory rules exist and this can lead to problems. Production rules have the advantage of allowing the expert system to stack up a record of a program's use of each rule and thus provide simple explanations of the systems reasoning. Production rules also make fairly light demands on a processor, although large amounts of memory or secondary storage will usually be required.

2.3.2 Data representation

All expert systems refer to data during their decision making. The representation of data can be simple or complex, depending on the problem. This section mentions four types of data representation scheme of varying complexity. The most basic scheme uses attribute-value pairs as shown in the rule in the production systems section. When a system is reasoning about multiple objects, it is necessary to have a slightly more complex scheme. In this situation objects as well as attribute-values must be included. Once there are objects in the system, they each might have multiple attributes. This leads to a record based structure where a single data item in the data base contains an object name and all the attribute-value pairs connected with it. One of the more complex schemes involves the use of frames for storing objects and their attribute-values. Frames add intelligence to the data representation, and allow objects to inherit values from other objects. Each of the attributes can have associated with it procedures (called demons) which are executed when the attribute is under study.
2.3.3 Goal-driven reasoning

Goal-driven reasoning, or backward chaining, is a method where a hypothesis is put forward and evidence is searched for to support or refute the hypothesis. It is an efficient way to solve a problem when the aim of the system is to pick the best choice from a certain number of possibilities. For example, most diagnostic systems fit this model, since the aim of the system is to pick the correct diagnosis. The rules of the knowledge base describe how each possible diagnosis might be selected. The rule reduces the large problem into smaller sub-problems. The commercial expert system PROSPECTOR uses goal driven reasoning to provide advice on mineral exploration. Another example of a commercial expert system is MYCIN which is used in medical diagnosis. One of the top level rules of MYCIN is shown below.

IF the infection is primary bacteremia and the site of the culture is one of the sterilesites and the suspected portal of entry of the organism is the gastrointestinal tract
THEN the identity of the organism is bacteroides.

The sub-goals of determining the infection, the site of the culture and the suspected portal of entry of the organism would either be satisfied by other rules or by asking the user. The user sees the system asking questions and responding to answers as it attempts to find the rule which correctly solves the problem.

2.3.4 Data driven reasoning

In many situations it is not feasible to describe all of the possible answers by rules and have the expert system select the correct one. An example of an expert system that uses data-driven reasoning is XCON (McDermott, 1982). XCON is an expert system for configuring computers. It starts with the data about the customer order and works forward toward a configuration based on that data. The rules used by a data-driven or forward chaining approach are similar to those used for backward chaining, but the reasoning process is different. The expert system moves forward through the rules in
the knowledge base while keeping track of the current state of the problem solution. The reasoning is driven by the features present and the input data. The system looks for rules which will move the current state closer to a final solution.

A data driven system must initially contain data unlike the goal driven system which collects data when it is required. Fig.[2.4] illustrates the differences between data driven and goal driven reasoning systems for two simple rules (taken from Merrit, 1989). The data driven system starts with the data of a=1 and b=2 and uses the rules to derive d=4. The goal driven system starts with the goal of finding a value for d and uses the two rules to reduce the problem to finding values for a and b.

2.3.5 Uncertainty

There are often times in goal driven reasoning systems when the final answer is not known with complete certainty. The rules written by the expert might not be clear and the user might not be sure of answers to questions. This is the case with medical diagnostic systems such as MYCIN, where the expert is not able to be sure about the relationship between symptoms and infectious diseases. The expert system PROSPECTOR also has to produce results when there is no certain answer. The expert system must locate sites where minerals exist based on uncertain information provided by the expert. Various theories have been developed to accommodate such uncertainty. One of the simplest solutions is to give each piece of information in the system an associated numerical value. The numerical value represents the certainty with which the information is known. The subject of uncertainty is not trivial and many methods have been used to deal with the problem of uncertain information.

2.3.6 User interface

The quality of the user interface is very important to the acceptability of an expert system. The simplest interfaces (such as the user interface of MYCIN) communicate with the user through a text screen containing scrolling dialogue. The user can enter commands, respond to questions and query questions asked by the system during the inference process. More sophisticated interfaces (such as MUNIN) use graphics screens to communicate with the user and incorporate pop-up menus, windows, mice,
Fig.[2.4]. The forward and backward chaining search strategy.
and similar facilities. MUNIN (Andreassen et al., 1987) is an expert system for electromyography and displays charts of the diseased states of a neuromuscular system.

2.3.7 Explanations

One of the main features of an expert system is its ability to explain its reasoning. An expert system is able to remember which rules were used during the inference process and can then provide those rules for the user to study as a means of explaining the results. The explanations can be very useful to the user in some expert systems, such as MYCIN. It would be able to present the subgoals found and justify how it came to a conclusion. In other expert system cases the explanations would not be so useful to the user. The expert system may only contain empirical knowledge and might not have any deep knowledge describing the problem domain to help the user understand the conclusions.

The explanation facility is always very useful to the expert system designer. The designer uses the explanations as a diagnostic tool during the development of the expert system. They allow the designer to trace through the knowledge bases of the expert system to see how the system is behaving and how the rules and data interact with each other.

2.4 Knowledge acquisition

Knowledge acquisition is work relating directly or indirectly to the acquisition of knowledge for an expert system (Gotts, 1984). Many techniques have been used in the past to acquire knowledge from the domain expert for medical expert systems. The most common method involves the use of interviews and observation studies. Interviews take a short time and provide information on the general principles used by the domain expert. Observation studies provide detailed information on real problem-solving behaviour. A number of interviews are usually required to gain a clear understanding of the problems that exist in a domain. Each interview should be recorded (for example by a tape recorder) so that no information is missed and detailed notes can be made after the interview. The methods used in discussions vary.
in the level of detail they concentrate on and the level of contribution given by the
domain expert and the knowledge engineer. Case studies should be examined during
the discussions and the knowledge engineer must observe the behaviour of the expert
during the solving of the problems. A mix of real and simulated case studies should be
used to cover as many different types of problems as possible. Welbank (1983) has put
forward a questioning strategy that can be used to acquire the knowledge from the
domain expert. The expert should be asked to :-

- (1) describe memorable problems that have occurred in past examinations.
- (2) distinguish between different diagnoses that have been made and describe
  what evidence was used to make the distinctions.
- (3) list symptoms and faults that are found during a diagnosis and the
  connections between them.
- (4) choose a typical case study and step through the reasoning used.
- (5) give a running commentary on the reasoning used during a real
  examination and record it. This is important, especially if the knowledge
  engineer is not allowed to sit in on the medical examination.

Gotts (1984) provides a detailed explanation of other methods that can be used in
knowledge acquisition and a review of the merits of the different approaches.

2.5 Top level design

There are four main technical objectives for the work :-

- (1) To classify all MUAP information in an EMG signal containing up to six
  MUs (recorded from a conventional needle electrode) with one hundred
  percent accuracy.
- (2) To decompose all superimposed waveforms containing overlapping
  MUAPs in an EMG signal.
- (3) To produce MUAP information that is not distorted by the decomposition
  method.
- (4) To design a decomposition method that produces fast and reliable results
  for the doctor.
The new decomposition method designed to achieve these objectives is split into three main stages. The first stage is the preprocessing of the EMG signal to extract MUAP activity from background noise. The EMG signal is filtered, normalised and segmented in this stage. The second stage is the classification of non-overlapping MUAPs in the signal. The final stage is the decomposition of overlapping MUAPs. This requires the use of an expert system. Knowledge for the expert system and for the classification of non-overlapping MUAPs was gained from literature on EMG analysis and from consultation with Dr. Brezinova, who is an expert in the field of electromyography at the EMG department of the Leicester Royal Infirmary.

The top level design of the new decomposition method is shown in Fig.[2.5]. The data flow diagram indicates how the processes are connected and how the information flows between processes. Chapter three describes the first two main stages of the decomposition method in detail. Chapter four describes the classification of overlapping MUAPs. Chapter five displays the results of the decomposition method. Appendix seven contains the main data flow and structure diagrams used in the software design of the new EMG decomposition method.
(1) Filtering of the EMG signal
(2) Normalising the processed signal
(3) Segmenting the normalised signal
(4) Classification of non-overlapping MUAPs
(5) Decomposition of superimposed waveforms

Fig.[2.5]. The top level data flow diagram for the decomposition method.
3.1 Introduction

This chapter describes a new method for the classification of non-overlapping MUAPs. The method tries to automatically extract MUAP waveforms from an EMG signal at force levels up to twenty percent of maximum voluntary contraction. The chapter initially describes a method that preprocesses the EMG signal for MUAP classification and then goes on to describe a new classification method.

3.2 MUAP data collection

EMG signals recorded using needle electrodes contain MUAPs with frequency components up to about 3kHz. Signals recorded using surface electrodes contain MUAPs with the frequency components up to only 800Hz (Desmedt, 1983). Active MUs near to the recording electrode produce MUAPs of large amplitude containing high frequency components while active MUs far from the recording electrode produce MUAPs of smaller amplitude containing lower frequency components.

An EMG signal recorded with a needle electrode is sampled at 10kHz and an EMG signal recorded with a surface electrode is sampled at 5kHz. An EMG signal recorded with a needle electrode is low pass filtered before it is digitised using a cut-off frequency of 5kHz to eliminate any anti-aliasing errors. The first stage of the MUAP data collection section accentuates the active MU firings from the noise and background activity. The EMG signal contains low frequency noise due to movement of the recording electrode in relation to the active MUs, and electrical noise due to other electrical activities in the vicinity. The second stage of the section normalises the EMG signal and the third stage segments the signal into regions of activity.

3.2.1 Filtering of the EMG signal

Two steps are used to filter the digitised signal. The first step acts as a high pass filter.
The filter known as a low pass differentiator (Usui and Amidror, 1982) has been
designed to suppress the noise caused by the electrode movement during recording.
The infinite impulse response filter uses a simple algorithm rather than a filter of
higher order to enable a fast implementation of the high pass filtering. The transfer
function of the filter is:

\[
H(z) = \frac{1 - z^{-1}}{1 - z^{-1}e^{-\sigma \tau}}
\]  

(3.1)

where \( \sigma \) = frequency range of EMG signal, \( \tau \) = sampling interval and \( z^{-1} \) is the
backward shift operator.

A high cut off frequency setting on the high pass filter can distort the EMG signal,
so a trade off is required between noise suppression and signal distortion. Fig.[3.1]
shows the frequency characteristics of the low pass differentiator. The cut-off
frequency of the filter (the 3db point) is set at 14 Hz. It is essential to use a filter which
causes minimum phase distortion of MUAP waveforms in an EMG signal, therefore
the filter has been designed with very small phase distortion within the passband.

The second step is a low pass filtering of the signal (Terrel, 1985). A finite impulse
response filter was designed to eliminate the effects of high frequency noise in the
EMG signal. A frequency-domain design was used with a Hamming window function.
Fig.[3.2] shows the ideal frequency response specified. The cut-off frequency is at
2500Hz and there is zero phase distortion. The sampling rates are approximately at
four times the maximum frequency components of the signal to allow the complete
description of the signal in the time domain. The specified amplitude/frequency and
phase/frequency characteristics of the filter were used to compute the impulse
response weighting sequence. The impulse response weighting sequence, \( g(i)T \), was
then multiplied by a Hamming window function \( W_r \) (see equation 3.2). The Hamming
window function reduces the oscillations in the amplitude/frequency characteristics,
(known as Gibbs phenomenon) which are caused by the truncation of the Fourier
series to \( N \) values. \( N \) was set at twelve.

\[
W_r = 0.54 + 0.46 \times \cos \left( \frac{r \pi}{3} \right)
\]  

(3.2)

\( r \) is the coefficient number of \( W_r \) and \( I (= 3) \) the number of terms either side of \( g(0)T \).
Fig.[3.1a]. The frequency characteristics of the low pass differentiator (magnitude).

Fig.[3.1b]. The frequency characteristics of the low pass differentiator (phase).
Fig.[3.2]. The ideal frequency characteristics of a low pass filter.
The resulting filter coefficients $g(i)W_r$ are shown below:

- $g(0)W = 0.500$  $W_0 = 1.000$  $g(0)W_0 = 0.500$
- $g(1)W = 0.312$  $W_1 = 0.770$  $g(1)W_1 = 0.240$
- $g(2)W = 0.000$  $W_2 = 0.310$  $g(2)W_2 = 0.000$
- $g(3)W = -0.083$  $W_3 = 0.080$  $g(3)W_3 = -0.006$

Therefore:

$$G(z) = -0.006 x z^3 + 0.24 x z^1 + 0.5 x z^0 + 0.24 x z^{-1} - 0.006 x z^{-3}$$

$z$ raised to a positive power represents a time advance and requires sampled data for $t < 0$. This is impractical and it is avoided by introducing a time shift so that the transfer function $G(z)$ contains no terms having $z$ raised to a positive power, that is

$$G(z) = z^{-3} x G(z)'$$

Therefore:

$$G(z) = -0.006 + 0.24 x z^{-2} + 0.5 x z^{-3} + 0.24 x z^{-4} - 0.006 x z^{-6}$$

$$\ldots \ldots \ldots \ (3.3)$$

The frequency characteristics of the filter are shown in Fig.[3.3].

Fig.[3.4] shows an EMG signal recorded using a needle electrode before and after the filtering steps. The filtered signal shows the reduction of baseline wander due to electrode movement. A reduction in high frequency noise is not so visible in this case.

### 3.2.2 Normalisation

The second stage of the MUAP data collection is a normalisation of the EMG signal. The normalisation is performed to reduce the complexity of the task required in the extraction of MUAP activity from the background noise later in the analysis. MUAP activity is extracted from the EMG signal by setting a triggering level.

The amplitude of the EMG signal recorded from person to person will vary dramatically and therefore a normalisation of the signal avoids triggering levels being set manually by the operator. Avoiding the problem of the manual setting of trigger levels also reduces noise in the EMG signal, due to the reduction in the amount of physical movement by the operator (the needle should be more still). The activity and
Fig.[3.3a]. The frequency characteristics of the low pass filter (magnitude).

Fig.[3.3b]. The frequency characteristics of the low pass filter (phase).
Fig.[3.4]. An EMG signal before and after filtering.
amplitude of the EMG signal are used as measures for normalising the signal. Initially, the maximum magnitude of the filtered signal is found and set to some standard value with the whole signal scaled accordingly. The background activity of the normalised signal is then studied to see the level of noise. The activity of the signal is a measure of the variation of amplitude with time (Gerber and Studer, 1984).

\[
\text{activity} = \sum_{i=n}^{n+m-1} |x_{i+1} - x_i| \quad (3.4)
\]

where \(x_i\) = magnitude of \(i^{th}\) sample and \(m\) = sample length of the study window (\(m = 100\) for the minimum activity and \(m = 6\) for the threshold level calculation).

The window is moved along the normalised signal, recording the activity. The minimum activity of the signal recorded is then used to find the triggering or threshold value. The algorithm required to perform the conversion from activity to threshold value was found by testing EMG signals with different noise levels and finding the required threshold levels needed to extract MUAP activity. Table[3.1] gives the results of the tests.

<table>
<thead>
<tr>
<th>EMG signal</th>
<th>threshold value required (mv)</th>
<th>minimum activity (mv)</th>
</tr>
</thead>
<tbody>
<tr>
<td>1</td>
<td>8.0</td>
<td>62.0</td>
</tr>
<tr>
<td>2</td>
<td>10.0</td>
<td>82.0</td>
</tr>
<tr>
<td>3</td>
<td>10.5</td>
<td>86.0</td>
</tr>
<tr>
<td>4</td>
<td>12.5</td>
<td>114.0</td>
</tr>
<tr>
<td>5</td>
<td>13.0</td>
<td>122.0</td>
</tr>
<tr>
<td>6</td>
<td>16.0</td>
<td>158.0</td>
</tr>
<tr>
<td>7</td>
<td>18.0</td>
<td>194.0</td>
</tr>
<tr>
<td>8</td>
<td>24.0</td>
<td>274.0</td>
</tr>
<tr>
<td>9</td>
<td>29.0</td>
<td>350.0</td>
</tr>
<tr>
<td>10</td>
<td>37.5</td>
<td>501.0</td>
</tr>
<tr>
<td>11</td>
<td>42.0</td>
<td>599.0</td>
</tr>
</tbody>
</table>

Table[3.1]. The relationship between background activity of EMG signals and the threshold level required to extract MUAP activity.
From these results, a curve fitting procedure was used to find the equation that best describes the relationship between the minimum activity (MA) and the threshold value (TV) required. The curve fitting procedure minimizes the error between the results and a general polynomial equation to find the coefficients of the polynomial equation. This is achieved using a method of least squares. Fig.[3.5] shows four graphs of the results with four best fitting curves described by different order polynomial equations. The equations are:

(a) \( MA = 15.6 \times TV - 81.0 \)

(b) \( MA = 0.135 \times TV^2 + 8.9 \times TV - 18.6 \) . . . . . . (3.5)

(c) \( MA = 0.003 \times TV^3 - 0.094 \times TV^2 + 13.8 \times TV - 49.1 \)

(d) \( MA = 0.00026 \times TV^4 - 0.023 \times TV^3 - 0.77 \times TV^2 + 2.18 \times TV + 3.68 \)

The second order polynomial equation was chosen to describe the relationship between the minimum activity and the threshold value. The curve fitted the experimental points with an average percentage error of 1.3. The equation was tested to see if it enabled the setting of automatic triggering levels. The results showed a successful setting of the triggering level in all cases tested.

3.2.3 Segmentation

The third stage of the MUAP data collection is a segmentation of the EMG signal into areas of activity and non activity. The areas of activity contain the motor unit action potentials. The areas of non-activity contain just background noise. The segmentation procedure follows work carried out by Gerber and Studer (1984). An EMG signal has time intervals when no MU firings have been recorded and there is an interval of no activity. To reduce data storage and reduce computational time for the later analysis the areas of non activity are disregarded. Each area of activity is classified as an active segment (AcS). The filtered signal is split into active segments using the same equation as the normalisation procedure.

\[
\sum_{i=n}^{n+m-1} |x_{i+1} - x_i| > \text{threshold} \quad . . . . . . . . . . (3.6)
\]
Fig[3.5a]. The curve fitting of a 1st order polynomial equation to the relationship between the background activity and the required threshold.

Fig[3.5b]. The curve fitting of a 2nd order polynomial equation to the relationship between the background activity and the required threshold.
Fig[3.5c]. The curve fitting of a 3rd order polynomial equation to the relationship between the background activity and the required threshold.

Fig[3.5d]. The curve fitting of a 4th order polynomial equation to the relationship between the background activity and the required threshold.
where $x_i$ = magnitude of $i^{th}$ sample length of the study window.

The threshold value for the onset of activity (calculated in the normalisation stage) is set at three times the threshold value for finding the end of activity. A factor of three was chosen after testing the algorithm on real data. Each active segment contains non overlapping or overlapping MUAP waveforms. Fig.[3.6] shows a real EMG signal recorded with a needle electrode (that has been normalised and filtered), before and after segmentation. The segmentation procedure can cope with low noise levels even after the filtering stage and therefore avoids the problems of setting tight limits on the filters and loosing some important MUAP information.

3.3 Classification of non-overlapping MUAPs

This section classifies non-overlapping MUAPs that exist as active segments into groups relating to the different active MUs that occur in an EMG signal. Active segments containing overlapping MUAPs are classed as superimposed waveforms and are not decomposed into their constituent MUAPs until the next section. The classification section is divided into seven stages.

3.3.1 Feature description

Every active segment formed from the last section is described by eight features. A relatively large number of features are used so that a fairly complete description of each active segment can be made. The eight features of each active segment are used to classify an active segment into an appropriate group. The use of a large number of features allows discrimination between similar active segment shapes containing MUAPs from different MUs, thus avoiding the problems encountered by previous methods (Mishelevich, 1970). The use of features instead of the actual data samples of an active segment dramatically reduces computational time. The eight features used are given below :-

(1) Maximum peak to peak amplitude.
(2) Maximum positive peak amplitude.
(3) Maximum positive slope.
Fig. [3.6]. An EMG signal before and after segmentation.
(4) Maximum negative slope.
(5) Number of turning points.
(6) Total positive area.
(7) Total negative area.
(8) Total number of samples.

The number of turning points (TPs) in an active segment refers only to the significant peaks in a segment. Small peaks arising from noise in the signal are not included. To achieve this goal, an algorithm has been designed to study the slopes of an active segment over a two sample span. By using a two sample span instead of calculating the slope from sample to sample small peaks due to noise are ignored. Fig.[3.7] shows a waveform described by twenty samples.

![Waveform](image)

**Fig.[3.7]. An active segment described by twenty samples.**

The algorithm finds the first TP in the waveform at $x_3$.

$$\text{sign}(x_3 - x_1) = +ve$$
$$\text{result} = +ve \text{ TP}$$

$$\text{sign}(x_5 - x_3) = -ve$$

The algorithm then searches for a TP of opposite sign and therefore ignores the next TP found, because it is positive.

$$\text{sign}(x_4 - x_2) = +ve$$
$$\text{result} = +ve \text{ TP}$$

$$\text{sign}(x_6 - x_4) = -ve$$
The next TP is located at \( x_{12} \).

\[
\text{sign}(x_{12} - x_{10}) = -\text{ve} \quad \text{result} = -\text{ve TP}
\]

\[
\text{sign}(x_{14} - x_{12}) = +\text{ve}
\]

No more TPs are found in the waveform and therefore the number of TPs located is two, representing a biphasic waveform. The other features of an active segment waveform are calculated in a straightforward manner. One of the problems with using features to represent an active segment is that the features may be correlated with each other. Some of the correlated features may therefore be given too much importance in the classification while providing limited extra information thereby producing less accurate results. For this reason Andreassen states that no two features carrying almost the same information should be included in the feature vector (1978). Under these circumstances some of the features should not be used to make a classification decision. Two factor analysis methods have been studied to try and resolve this problem.

3.3.2 Factor analysis methods

The first method is known as diagonal factor analysis. The method forms uncorrelated variables (or factors) from a larger number of correlated variables (or features). The formation of uncorrelated factors from eight correlated features would overcome the problems mentioned above. Diagonal factor analysis is the simplest factor analysis method where each factor is equal to a variable (or feature) multiplied by a weighting.

A feature is selected as a factor when it has the highest squared correlations between itself and other features. The first factor is assumed to be the equivalent of the selected feature. The extent to which this one factor carries the same information as the other features is determined by analysing the correlation matrix formed from all the active segments. The next factor is then set equal to the second selected feature and the variance that it can account for (and therefore the weighting given to it) is determined by the correlation matrix from which the variance for the first factor has been extracted. The process is then continued until all the factors are found (Gorsuch, 1974).
The second method is known as principal component (or factor) analysis. The method extracts the maximum amount of variance that can be possibly extracted from correlated variables (for example eight features) by a given number of uncorrelated variables (or factors). Each factor accounts for the maximum possible amount of the variance of the features being factored. This method would also overcome the problems mentioned above.

Principal component analysis is one of the most common methods used for forming a small number of uncorrelated variables (or factors) to describe a larger number of correlated variables (for example - Jones, Lago and Parekh, 1985). This is because it finds the smallest possible number of uncorrelated variables (or factors) to describe a number of correlated variables. The method uses the characteristic roots and vectors of the feature correlations and involves a great deal of calculations.

In this case, the principal component (or factor) analysis method would form a (8x8) feature correlation matrix from all the active segments. The factor that accounts for the maximum amount of variance of the features is then found. The factor consists of a weighted combination of all features which will produce the highest squared correlations between the features and the factor. (The squared correlation is a measure of the variance accounted for). The second factor is extracted so that it is uncorrelated with the first factor. This factor maximises the amount of variance extracted from the correlation matrix after the effect of the first factor has been removed. Each succeeding factor is extracted in like manner, and so a small number of factors account for as much of the variance as that number possibly could (Gorsuch, 1974).

In this particular application the criterion is to form uncorrelated factors from eight features and therefore avoid the problems of incorrect MUAP classification. The criterion is not to find the smallest possible number of uncorrelated factors that can describe the eight correlated features. It was therefore decided to use diagonal factor analysis as part of the MUAP classification method because of its simplicity and avoid the need for the large computations required in principal component analysis. The next section describes the details of the diagonal factor analysis procedure. The work is derived from Gorsuch (1974) and Hunter (1972).
3.3.3 Diagonal factor analysis

Firstly, the features describing all the active segments (AcSs) are standardised and the mean values eliminated. The correlation matrix is then formed from the standardised features of all the active segments. Correlation measures the association between two variables. Pearson’s product moment correlation coefficient ($\rho$) is used as the parametric measure of linear association between two variables $X_1$ and $X_2$. It is defined as the ratio of the covariance between two variables to the square root of the product of the two variances ($\sigma_1^2$, $\sigma_2^2$)(King and Julstrom, 1982). Thus

$$\rho_{12} = \frac{\text{Cov}(X_1, X_2)}{(\sigma_1^2 \cdot \sigma_2^2)^{1/2}} = \frac{\text{Cov}(X_1, X_2)}{\sigma_1 \cdot \sigma_2} \ldots \ldots \ldots \ . (3.7)$$

For sampled data, an unbiased estimate, $r_{12}$, of the correlation coefficient is:

$$r_{12} = \frac{N \sum (X_1 X_2) - \sum X_1 \cdot \sum X_2}{(N \sum X_1^2 - (\sum X_1)^2) \cdot (N \sum X_2^2 - (\sum X_2)^2)^{1/2}} \ldots \ . (3.8)$$

where $X_1$ and $X_2$ are the numerical values of two features and $N$ is the number of AcSs. $\Sigma X_1$, for example is the summation of the numerical value of the feature $X_1$ from $N$ active segments. The coefficients $r$ vary from +1.0 (perfect positive correlation) through to zero (no correlation) to -1.0 (perfect negative correlation).

Next, the sum of squared correlations for each column of the correlation matrix is found. The sum of squared correlations with the other features indicates how much of the other features can be predicted from a diagonal factor defined by the feature associated with a particular column. The feature with the highest sum of squared correlations with the other features is selected. The selected feature defines the first diagonal factor and is the feature which carries most information about the other features. The weighting given to the first diagonal factor is the square root of the associated auto covariance (unity). Fig.[3.8] shows the column with the highest sum of squared correlations and the weighting of the first diagonal factor (highlighted with a box). The diagonal factor analysis method then forms a second diagonal factor. The second diagonal factor accounts for variance in the correlation matrix which is not
The feature correlation matrix formed from all the active segments.

**Fig.[3.8]**

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</table>

The residual matrix of the active segments.

**Fig.[3.9]**

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</table>
accounted for by the first diagonal factor. The effect of the first diagonal factor is eliminated from the correlation matrix to form the residual matrix (see Fig.[3.9]) according to equation (3.9) given below.

\[ R_{ij,A} = R_{ij} - P_i \cdot P_j \]  
\[ \ldots \ldots \ldots \ldots \ldots \ldots \ldots \ldots \ldots \ldots \ldots \ldots \ldots \ldots \ldots \ldots \ldots \ldots \ldots \ldots \ldots \ldots \ldots \ldots \ldots \ldots \ldots \ldots \ldots \ldots \ldots \ldots \ldots \ldots \ldots \ldots \ldots \ldots \ldots \ldots \ldots \ldots \ldots \ldots \ldots \ldots \ldots \ldots \ldots \ldots \ldots \ldots \ldots \ldots \ldots \ldots \ldots \ldots \ldots \ldots \ldots \ldots \ldots \ldots \ldots \ldots \ldots \ldots \ldots \ldots \ldots \ldots \ldots \ldots \ldots \ldots \ldots \ldots \ldots \ldots \ldots \ldots \ldots \ldots \ldots \ldots \ldots \ldots \ldots \ldots \ldots \ldots \ldots \ldots \ldots \ldots \ldots \ldots \ldots \ldots \ldots \ldots \ldots \ldots \ldots \ldots \ldots \ldots \ldots \ldots \ldots \ldots \ldots \ldots \ldots \ldots \ldots \ldots \ldots \ldots \ldots \ldots \ldots \ldots \ldots \ldots \ldots \ldots \ldots \ldots \ldots \ldots \ldots \ldots \ldots \ldots \ldots \ldots \ldots \ldots \ldots \ldots 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sequence according to the similarity of the vectors representing the shapes of the AcSs. The euclidean distance (ED) between two vectors representing two AcSs is the measure used to study this similarity.

$$ED_{xy} = \left( (x_1 - y_1)^2 + (x_2 - y_2)^2 + (x_3 - y_3)^2 + \ldots \right)^{\frac{1}{2}} \ldots (3.11)$$

where $x_i$ are the orthogonal coordinates (diagonal factors) of one AcS under consideration and $y_i$ are the orthogonal coordinates of the other AcS under consideration. The last AcS in the EMG signal is chosen as the first segment in the network to be formed and the euclidean distances between it and all the other AcSs are calculated. The minimum of all the euclidean distances is found and the AcS defining that distance is added to the network. Next, the smaller magnitude of these two vectors is calculated. The distance measure used to describe the similarity between adjacent AcSs in the network is then the minimum euclidean distance divided by the smaller of the two vector magnitudes and is called the network distance (ND).

$$ND_x = \frac{\min (ED_{xy})}{\text{vectorlength}} \ldots \ldots \ldots \ldots \ldots \ldots \ldots \ldots \ldots \ldots \ldots (3.12)$$

The above procedure is repeated for each AcS last connected to the network. AcSs cannot exist at more than one point in the network. Fig.[3.10] shows the formation of a network from AcSs extracted from an EMG signal containing two MUs. AcSs containing non-overlapping MUAPs from the same MU are grouped together. The method has the ability to group together MUAPs from the same MU and allows for the fact that MUAPs gradually change in shape over time due to electrode movement. The method also caters for situations in diseased states when the variability of the MUAP shapes from a MU is much larger than for a normal case.

3.3.5 Clustering of non-overlapping MUAPs

The next stage of the classification section is to use the network information to form groups of AcSs, where each group contains non-overlapping MUAPs from the same MU. To do this the network must be divided into clusters. Fig.[3.11] shows the network distances formed from Fig.[3.10]. The network is cut where the network distance increases abruptly, thus forming groups of AcSs. This is achieved by studying
Fig. [3.10]. The network formation of the EMG signal.

Fig. [3.11]. The network distances of the EMG signal.
the variation in the distances of the network (see Fig. [3.11]). The algorithm used, searches for distances in the network that are significantly larger than the average of the next four consecutive distances. The smallest distance found from the search is then used as the threshold level for splitting the network into groups.

If the number of AcSs in a cluster group is below five or their network distances are above the threshold value, the AcSs of the group are classed as superimposed waveforms. Fig. [3.11] shows one of the network distances between MUAPs from the same MU having a distance greater than the set threshold level and thus one MUAP was classed as a superimposed waveform. This is because of the high level of noise that has corrupted the MUAP shape in question. If the number of AcSs in a cluster group is above five and their network distances are below the threshold value, the AcSs are classed as MUAPs from the same MU. The value five was chosen because it was large enough to be fairly certain that the AcSs are MUAPs from the same MU and not waveforms (containing either superimposed waveforms or noise) that happen to be similar in shape by chance. The average MUAP waveform of the cluster group is then calculated using the actual data samples of the AcSs rather than the features. Two different methods are used to form an average waveform from the grouped AcSs and a comparison of the results is shown in the section below.

Fig. [3.13] shows two network distance graphs formed from the EMG signal displayed in Fig. [3.12]. The difference between the two graphs is that Fig. [3.13b] uses factor analysis to weight each active segment vector while Fig. [3.13a] uses active segment vectors not weighted by the factor analysis. It can be seen that the network distance graph in Fig. [3.13b] discriminates clearly between AcSs containing MUAPs from different MUs while the graph in Fig. [3.13a] makes less clear the three regions where the three MU groups exist.

The use of weighted features enables the correct classification of the three MU groups present in the EMG signal. Active segments that are either noise or superimposed waveforms formed from overlapping MUAPs are not classified. The use of non-weighted features in this instance results in a miss classification of the number of MU groups present in the EMG signal. Only two MUs are classified. The other active segments are classed as superimposed waveforms. The superimposed
Fig. [3.12]. An EMG signal containing three MUs with each active segment extracted labelled.
The active segment groups are:

25 22 20 14 13 5 9 18 16 4 11 8 15 24 21 19 0 23 6 12 17

Fig. [3.13a]. The network distances of the EMG signal using unweighted features.

The active segment groups are:

25 22 20 14 3 7 10 13 5 9 18 16 4 11 8 15 24 21 19 0 23 6 12 17

Fig. [3.13b]. The network distances using weighted features.
waveform in the signal (number sixteen) formed from two overlapping MUAPs is also classed incorrectly as a non-overlapping MUAP. This example emphasises the importance of using diagonal factor analysis in conjunction with the feature description of an active segment to produce accurate classification results.

### 3.3.6 Active segment averaging

**i) Dynamic time warping** - Problems might arise when finding the average waveform of a group of active segments, due to incorrect alignment of the waveforms. Different active segments in a group might be of slightly varying amplitude and time duration because of electrical noise present in the signal and because of the movement of the recording electrode relative to the active MUs.

To overcome these problems a non-linear time alignment technique known as dynamic time warping can be used (Bellman and Dreyfus, 1962). Dynamic time warping allows portions of a signal to be stretched and shrunk to make the two sequences as similar as possible. Dynamic time warping has been used in the past to align evoked potentials (Picton et al., 1988), to assist in classifying patterns in spontaneous EEG (Haung and Jansen, 1985) and in measuring morphological changes in the somatosensory EP (Eisen et al., 1986). The process of averaging two waveforms using dynamic time warping involves several steps (Fig.[3.14]). The explanation is derived from Picton et al. (1988).

Firstly, the waveforms being averaged must be of the same number of samples, therefore the shortest waveform is padded out with zeros to make the lengths equal. Next, the waveforms are normalised, in order to compensate for scaling differences between waveshape. This is achieved by removing the mean value \( u \) and dividing the result by the root mean square value for each waveform.

\[
\hat{a}_i = \frac{a_i - u}{\sum a_i^2} \quad (3.13)
\]

where \( a_i \) is the amplitude of the \( i^{th} \) value of a waveform and \( \hat{a}_i \) is the amplitude of the \( i^{th} \) value of the normalised waveform.
Fig. [3.14]. Diagrammatic representation of dynamic time warping.
In order to find a non-linear alignment of the waveforms that will make them as similar as possible in terms of amplitude, a dissimilarity measure is defined between the \( j \)th sample of waveform \( X \) and the \( k \)th sample of waveform \( Y \) as the sum of the absolute differences in \( a^* \).

\[
d_{jk} = |a^*(X_j) - a^*(Y_k)| \quad \ldots \ldots \ldots \ldots \quad (3.14)
\]

The alignment that minimizes the sum of this dissimilarity measure along the waveforms is then found. If \( X \) is plotted horizontally with time increasing from left to right and \( Y \) plotted vertically with time increasing from top to bottom, then possible alignments can be represented as monotonically increasing paths extending from point \((1,1)\) in the top left corner to point \((j,k)\) in the lower right corner. The task is then to find the path over which the summed dissimilarity measure is a minimum.

An individual step in a path can be vertically downwards (from \( j,k \) to \( j,k+1 \)), horizontally rightwards (from \( j,k \) to \( j+1,k \)) or diagonally downwards and rightwards (from \( j,k \) to \( j+1,k+1 \)). \( D_{jk} \) is defined as the minimum summed dissimilarity measure from \( 1,1 \) to \( j,k \). This value can be computed from its precursor values using the relation:

\[
D_{jk} = d_{jk} + \text{MIN}(D_{j,k-1}, D_{j-1,k}, D_{j-1,k-1}) \quad \ldots \ldots \ldots \quad (3.15)
\]

where \( j \) and \( k > 1 \). The function MIN selects the minimum of its three arguments, with the following rules for the left edge and the lower edge of the matrix.

\[
D_{j,1} = d_{j,1} + D_{j-1,1} \quad \text{where} \quad j > 1.
\]

\[
D_{1,k} = d_{1,k} + D_{1,k-1} \quad \text{where} \quad k > 1.
\]

\[
D_{1,1} = d_{1,1}.
\]

By applying these relations recursively from point \( 1,1 \) to point \( j,k \) the total dissimilarity along the optimum alignment path \( D_{j,k} \) can be found.

A matrix of pointers is also stored showing for each position the direction from which the optimum path has come to that position. The optimum path can be determined by constructing a \( j \times k \) matrix whose \( j,k \)th element indicates which of the
three possible points immediately precede j,k along the optimum path passing through j,k. The optimum path is revealed by tracing back from j,k along the set of pointers defined by this matrix.

**ii) Median averaging** - Median averaging is a simple method that forms the averaged waveform from a group of active segments by aligning the maximum peaks of the active segments and then finding the median value of each sample point. The active segments are aligned by shifting them in time. The median value of each sample point in the time shifted active segments is obtained by arranging the sample values for that point in ascending order and finding the value at the half way point in the ordered array (Nandedkar and Sanders, 1989).

**iii) MUAP averaging results** - The two averaging methods were tested on real and simulated EMG signals with different levels of SNR. Dynamic time warping is a slow method of averaging in comparison with median averaging. Fig.[3.15] shows the averaged waveform of AcSs taken from an EMG signal using the two different methods. It can be seen that the median averaging and dynamic time warping methods form an averaged waveform that is a good representation of the active segments that form it. In a situation with very high levels of background noise the dynamic time warping method proved to be slightly more effective than the median averaging method because of the badly distorted active segments recorded. These situations occur very rarely in practice and it was therefore decided to use the median averaging method to form average MUAP waveforms because of speed considerations.

**3.3.7 MU statistics**

Next, the firing statistics of the MUs classified in the last stage are calculated. The firing period information from a MU cluster could be represented as a histogram, as shown in Fig.[3.16]. Unclassified MUAPs due to superpositions will produce varying firing periods. The mean and standard deviation of the firing periods of each MU cluster are calculated using only the information from the consecutively occurring non overlapping MUAPs.

The criterion used to group together firing period values of a MU is that the periods are within plus or minus twenty percent of each other. The range of plus and minus twenty percent was chosen because of MUAP train studies that have been
Fig.[3.15]. The results of finding the average waveform of AcSs by using median averaging and dynamic time warping.
Fig.[3.16]. A histogram of the firing period statistics of a MU.
undertaken previously by other researchers (Andreassen and Rosenfalck, 1980). Groups will form representing the different components of the histogram shown in Fig.[3.16]. The mean and standard deviation of each group is calculated. The group with the smallest mean firing period is used to represent the true firing statistics of the MU.

3.3.8 Merging of similar MUs

At this stage of the analysis, different MU groups and superimposed waveforms have been formed. A situation might occur where a MU group has been divided into different groups by the analysis. This could be due to noise from excessive electrode movement, causing the network distance between two MUAPs from a MU to be larger than the threshold value and thus not forming one MU group.

To compensate for this problem, the clustered MU groups are studied for similarity of MUAP shape and firing statistics. If two clustered MU groups are similar in MUAP shape and mean firing period the two groups are merged to form one larger MU group. The criteria used to decide if two MU groups should be merged to form one group are given by the two equations below.

\[
\frac{ED_{xy}}{VL_x} < 0.1 \quad (3.16)
\]

where \( ED_{xy} \) = euclidean distance between the two vectors, describing the average MUAP waveforms of the two MUs and \( VL_x \) = length of smaller MU vector.

and

\[
\left| \frac{MFP_x - MFP_y}{MFP_x} \right| < 0.1 \quad (3.17)
\]

where \( MFP_x \) = mean firing period of a MU.
CHAPTER 4 Design method for the classification of overlapping MUAPs

4.1 Introduction

At high force levels only a few non-overlapping MUAPs exist. Therefore, the information gained from the classification of non-overlapping MUAPs may not be sufficient to allow a clinician to make a diagnosis. To validate the results of the MUAP classification, superimposed waveforms containing overlapping MUAPs are decomposed into their constituent MUAP waveforms to extend the information already collected. The new method of decomposing superimposed waveforms formed by overlapping MUAPs tries to produce fast and accurate results.

With current methods of decomposition either errors will result, the time taken for decomposition is very long (LeFever and DeLuca) or much training is required to use the decomposition scheme. Errors could be due to noise in the signal or because of the similarity between results after a pattern matching analysis.

Human experts are able to identify which of the possible MUAP combinations comprise a superimposed waveform by studying the firing times of the MUAP trains (Basmajian and DeLuca, 1985). Typically they would arrive at a decision based on uncertain and incomplete evidence available from the MU information already classified. This observation has led to the specification of an expert system (DEMGES) which uses a fuzzy reasoning model to describe the decomposition protocol of superimposed waveforms. DEMGES is an acronym for Decomposition of an EMG Expert System.

The decomposition of superimposed waveforms is divided into two sections. The first section is a procedural method that finds a reduced set of all possible combinations of MUAPs which are capable of forming each superimposed waveform by using a template matching procedure. The second section is the knowledge based analysis of the candidate MUAP combinations forming each superimposed waveform. This latter analysis decides which combination is the most probable (see Fig.[4.1]).
MUAP templates as provided by non-overlapping MUAP classification stage

MUAP 1

MUAP 2

MUAP 3

MUAP 4

MUAP 5

Superimposed waveform

MUAP train information

MUAP 4

MUAP 2 & MUAP 3

MUAP 1 & MUAP 2 & MUAP 5

MUAP 2 & MUAP 5

RULE BASED EXPERT SYSTEM

( DEMGES )

candidate MUAP combinations from procedural decomposition stage

Most probable MUAP combination is MUAP2 and MUAP3 cf 0.8

Fig.[4.1]. Functional diagram of the DEMGES expert system.
4.2 Procedural analysis

The procedural analysis is split into two sub-sections. The average MUAP waveform from each clustered MU group is used as a MUAP template in this section. Only superimposed waveforms containing up to three MUAPs can be successfully decomposed with this analysis. Decomposing superimposed waveforms containing more than three MUAP constituents would dramatically increase computational time and is therefore not attempted.

4.2.1 Combination reduction

The first stage reduces the possible MUAP combinations that could form a superimposed waveform. The method uses the fact that MUAPs forming a superimposed waveform will have a total area sum equal to that of the superimposed waveform (see Fig.[4.2]). The criteria used to select a MUAP combination as possibly forming a superimposed waveform is given below.

\[ |T_{Amc} - T_{Asw}| < \text{threshold} \quad \ldots \ldots \ldots \ldots \ldots \quad (4.1) \]

where \( T_{Amc} \) = total area of a MUAP combination and \( T_{Asw} \) = total area of a superimposed waveform. Single MUAPs are still considered as possible waveforms that might form a superimposed waveform, as noise components may have prevented a detection earlier in the analysis. MUAP combinations selected from this stage are passed onto to the next optimisation stage.

4.2.2 Optimisation

This second stage of the procedural analysis further reduces the possible MUAP combinations forming a superimposed waveform selected from the first stage. The selected MUAP combinations from stage one are used in a template matching scheme with the superimposed waveform. The template matching procedure is similar to the method by LeFever and DeLuca (1982) and finds the residual error between a MUAP combination and the superimposed waveform by subtracting each MUAP in the combination from the superimposed waveform. Each subtraction is performed by aligning the maximum peak of the superimposed waveform with the maximum peak
Total area of a waveform is $\text{MUAP}_1$ minus $\text{MUAP}_2$.

A possible superimposed waveform:

\[ \text{superimposed waveform} = \text{residual waveform} \]

\[ \text{subtract} \]

\text{1st MUAP in combination}

\[ \text{subtract} \]

\text{2nd MUAP in combination}

\text{residual error}

Fig.[4.2]. The relationship in area between a superimposed waveform and its MUAP constituents.

Fig.[4.3]. The subtraction of two MUAPs from a superimposed waveform.
of one MUAP in the combination until all the MUAPs in a combination have been subtracted. If the final residual error is below a set threshold level, the MUAP combination is selected for the knowledge based analysis. Fig. [4.3] shows the subtraction procedure for a combination of two MUAPs. To reduce errors when aligning MUAPs with a superimposed waveform, the order in which the MUAPs are subtracted from the superimposed waveform is changed and the subtraction repeated to find the smallest residual error of the MUAP combination.

### 4.3 Knowledge based analysis (DEMGES)

DEMGES makes a final decision on which MUAPs are most likely to form a superimposed waveform by studying how the firings of the candidate MUAPs fit in with the firing time statistics of the MUs. DEMGES contains four main modules: the data base, the knowledge base, the interpreter and the user interface (described later). DEMGES uses fuzzy certainty factors to model its uncertain reasoning mechanism so that an intelligent decision can be made. The fuzzy certainty factors are calculated using fuzzy set theory. The fuzzy membership functions are described by the firing period statistics of the partially classified MUs. Bayesian decision theory was not used because a priori probability values do not exist for the MUAP combinations. It also assumes independence between the MUs which is not always true.

The rules that DEMGES contains are modelled on the judgemental processes that an expert uses for superimposed waveform decomposition. MUAP candidates in a combination, selected from the procedural analysis, are given fuzzy values which are propagated through the search space towards the final goal of finding the certainty of a MUAP combination forming a superimposed waveform. Hence, the procedural analysis results are easily assigned qualitative descriptions for the expert system to reason with. The method by which fuzzy values are assigned to the MUAP combinations relies on the definition of a fuzzy model describing the EMG signal.

#### 4.3.1 Fuzzy Set Theory

Fuzzy set theory, introduced by Zadeh (1965), is a generalisation of abstract set theory. Definitions, theorems, proofs, etc. of fuzzy set theory always hold for non-fuzzy sets. Because of this generalisation, fuzzy set theory has a wider scope of
applicability than abstract set theory in solving problems which involve, to some
degree subjective evaluation. The following explanation of fuzzy set theory is taken
from Wang and Chang (1980). Intuitively, a fuzzy set is a class which admits the
possibility of partial membership in it. Let $\Omega = \{x\}$ denote a space of objects. Then a
fuzzy set $A$ in $\Omega$ is a set of ordered pairs

$$ A = \{(x, \Pi_A(x)) \}, \quad x \in \Omega \quad . . . . . . . . . . . . . . . \quad (4.2) $$

where $\Pi_A(x)$ is termed the grade of membership of $x$ in $A$. It is assumed for
simplicity that $\Pi_A(x)$ is a number in the interval $[0,1]$, with the grades 1 and 0
representing respectively, full membership and non-membership in a fuzzy set. It is
assumed that an exact comparison is possible for the truths of any two inexact
statements $x \in A$ and $y \in A$ and that the exact relation so obtained satisfies the minimal
consistency requirements of transitivity and reflexivity.

The union of two fuzzy sets $A$ and $B$ in $\Omega$ is defined as the membership function of
$A+B$ given by

$$ \Pi_{A+B}(x) = \max[\Pi_A(x),\Pi_B(x)] \quad . . . . . . . . . . . . . . . \quad (4.3) $$

The intersection of $A$ and $B$ in $\Omega$, denoted by $A*B$, is defined similarly by

$$ \Pi_{A*B}(x) = \min[\Pi_A(x),\Pi_B(x)] \quad . . . . . . . . . . . . . . . \quad (4.4) $$

In order for ordinary set theory to remain a special case of fuzzy set theory it is
required that not(0) = 1 and not(1) = 0, not[not(\Pi)] = \Pi, and not be continuous and
strictly monotonic decreasing since the subjective evaluation of not $x$ should decrease
when our evaluation of $x$ increases.

$$ \Pi (\text{not } x) = 1 - \Pi(x) \quad . . . . . . . . . . . . . . . \quad (4.5) $$

4.3.2 The Fuzzy Procedural Model (Data Base)

The fundamental primitive for information modelling is propositional statements
of the form: an attribute of an object has a particular value. This is represented in the
Prolog language as the symbolic structure :-

Object Attribute Value
Again in Prolog, we may express that a MUAP candidate in a combination definitely occurs at exactly the position of a superimposed waveform X by writing:

\[ \text{MUAP position_is X} \]

This will not be the case in reality, because the firing times of a MU are not exactly regular. The MUAP candidates are given fuzzy values related to the possibility of a MUAP occurring at the position of a superimposed waveform. The fuzzy value is calculated using the fuzzy membership function shown in Fig.[4.4]. This function can be described in terms of a fuzzy set.

### Fig.[4.4]. The fuzzy membership function.

The fuzzy value of a MUAP candidate is calculated by mapping the smallest firing period (SFP) between the nearest neighbouring MUAP in the MUAP train and the position of the superimposed waveform onto the fuzzy membership function which describes the MU firing period distribution. In Fig.[4.4] for example, a MUAP candidate ‘A’ maps to a fuzzy value of 0.9 indicating partial membership of the fuzzy set of all possible firing periods. The duration of the fuzzy function varies for each MUAP train (and hence each MU) in the EMG signal, depending on the mean and standard deviation of the firing period of the MU duration.
4.3.3 The Fuzzy Declarative Model (Knowledge base)

This model attempts to capture the expert decision making process used to decompose superimposed waveforms. The fuzzy procedural model above makes it possible to formulate propositions of the form :-

Object Attribute FuzzyValue

FuzzyValue = Value + Fuzz

Furthermore we can formulate the consequence of fuzzy propositions in Prolog by using fuzzy rules of the form:

if Object Attribute FuzzyValue
then ObjectX AttributeX ValueX.

The value ValueX of object ObjectX is asserted with the fuzzyness Fuzz (in FuzzyValue) of object Object. The modeller is also allowed to express the reliability or confidence in a rule being true through a rule attachment called a certainty factor, cf.

if Object Attribute FuzzyValue
then ObjectX AttributeX ValueX cf CF.

In this case, the value ValueX of object ObjectX is asserted with the minimum value of the fuzzyness Fuzz (in FuzzyValue) of object Object and the cf attachment CF.

\[ FuzzX = \min (Fuzz, CF) \] \hspace{1cm} (4.6)

The premise of a rule can contain both conjunctions and disjunctions of propositional clauses. The combined fuzzy value of a conjunction or disjunction of clauses is determined using fuzzy set theory. In a conjunction the minimum fuzzy value is taken from the computed fuzzy values in the set of clauses in the premise. In a disjunction the maximum fuzzy value is taken.
The example below shows a rule containing a conjunction of two propositional clauses and the conclusion of the rule being given a confidence or certainty factor.

\[
\text{rule19 ::} \\
\text{if} \\
\text{Mean} \ < \ (SFP / 1.5) \ \text{and} \\\n\text{Firing\_period} \ \text{is} \ (SFP / 2.0) \\\n\text{then} \\
\text{muap( MuapNo, Mean, SD, FiringPeriod ) is\_compared\_with SFP cf 0.95.}
\]

Some rules in the knowledge base (e.g. rule19 above) cater for problems that arise when the smallest firing period (SFP) between the nearest neighbouring MUAP and the position of the superimposed waveform is much greater than the mean firing period of the MU (due to unclassified MUAPs), as shown in Fig.[4.5]. This is done by repeating the fuzzy membership function at multiples of the mean firing period. These rules are given certainty factors (or confidence values) that reduce in value as the SFP increases with respect to the mean firing period of a MU. Fig.[4.6] shows the effect on confidence in the rules at increasing multiples of the mean firing period of a MU. (The confidence values for increasing SFPs were arbitrarily chosen).

This behaviour is captured in DEMGES by using additional rules similar to rule 19 above, each having a different cf value. The ordering of the rules in the knowledge base and Prolog's in-built backtracking control mechanism results in the gradual decay of confidence values being produced. Other rules determine the effect a MUAP's position has on the outcome of the result. These rules calculate the overall fuzzy value (or possibility) of each candidate MUAP combination (Z) forming a superimposed waveform. The formula used to find the overall fuzzy value is:

\[
F(Z) = F(X) \times \text{NOT}(F(Y)) \quad \ldots \quad \ldots \quad \ldots \quad \ldots \quad (4.7)
\]

where \(F(Z)\) is the overall fuzzy value of a MUAP combination, \(F(X)\) is the combined fuzzy value of the intersection set of individual MUAPs in a combination and \(F(Y)\) is the combined fuzzy value of the exclusive set of individual MUAPs not in a combination.
Fig.[4.5]. Firing times of a MU before decomposition of superpositions.

Fig.[4.6]. The confidence values of rules.
4.3.4 The DEMGES Interpreter

The interpreter shell is backward chaining and provides uncertain inference and explanation capabilities on the declarative model described in the previous section. It also provides the interfacing with the procedural model through invocation of user-defined procedures. The interpreter manipulates and executes Prolog expressions making up the declarative model (ie. knowledge base) and passes goals such as the user-defined procedures to Prolog for execution. The use of user-defined procedures is necessary for the evaluation of mathematical constructs and for interfacing to the ‘C’ language which performs the initial numerical analysis.

An important specification for this implementation has been the separation of all DEMGES modules. In this respect the same interpreter can be used to execute knowledge bases that will be defined in the future for further interpretation of results produced by DEMGES and for diagnostic purposes. The structure of the interpreter shell is derived from the work by Sehmi (1988) and Sehmi and Jones (1989).

%Top call
solve(Goal) :-
solve(Goal cf Fuzz, Fuzz, []).

%Is goal known
solve(Goal cf Fuzz, Fuzz, _ ) :-
fact :: Goal cf Fuzz.

%Is goal solvable using a procedural call
solve( Goal cf Fuzz, Fuzz, _ ) :-
proc(Goal,User_defined_procedure),
call(User_defined_procedure).

%Is goal solvable using a rule
solve(Goal cf Fuzz, Fuzz, Stack) :-
Rule :: if Premise then Goal,
satisfy(Premise, Fuzz, [Goal+Rule|Stack]),
conclude(Goal,Fuzz,Rule).

%Ask user for solution
solve(Goal cf Fuzz, Fuzz, _ ) :-
askable(Goal),
assert_solution(Goal).

Satisfy/3 attempts to solve the clauses in Premise by recursively invoking solve/3 with each clause in turn. A successful goal will cause satisfy/3 to calculate its certainty (or fuzzy) value and eventually a combined certainty value for all the clauses in Premise. Conclude/3 will then assert the Goal into the database with the combined certainty value of Premise.

4.3.5 The User Interface

The user interface provides the facility to query the results of the EMG signal decomposition. Fig.[4.7] shows a simulated EMG signal containing four motor unit trains. The suggestion that a superimposed waveform contains MUAPs two and three has been queried by selecting the waveform in the EMG signal using a mouse pointing device. A pop-up window shows the fuzzy certainty values of the result and all the other possible combinations of MUAPs that could have formed the selected superimposed waveform. The user is given the option to study how the conclusions were formed. The how explanation displays the trace of reasoning taken by the expert system by interpreting the proof-tree built up in reaching that conclusion. The user is also able to study any rule invocations to seek a more specific explanation to a query. Fig.[4.8] and Fig.[4.9] show the facilities available in the user interface of the expert system. The window based interface provides a help facility (see Fig.[4.8]) for the user as an aid to studying the rules of the expert system. Fig.[4.9] shows the user querying one of the clauses in the rule displayed.
Fig.[4.7]. The explanation user interface with DEMGES.
The help facility can be called through the pop-up menu or from the explanation module by typing in 'help'. The explanation module can be exited by pressing the ESCAPE key. The pop-up menu can also be exited in this fashion.

**EXAMPLE**

\[ \text{muaps}(1,2) \text{ form}_\text{superposition}. \]
\[ \text{muaps}(2,4) \text{ form}_\text{superposition}. \]
\[ \text{muaps}(1,2) \text{ has}_\text{highest}_\text{certainty} \ 0.89. \]

Which fact would you like to query ('c.' to continue)?

\[ \text{muaps}(2,4) \text{ form}_\text{superposition}. \]

help.

Fig.[4.8]. The help facility of the expert system DEMGES.
THE EXPERT SYSTEM 'DEMGES' IS

rule1::
if
get_combination comb9
and comb9 superposition_sfps_are super([012.000000,712.00
0000,144.000000,0.000000])
and comb9 combination_contains muaps(1,2,3)
and 3 muaps_in_combination comb9
and super([012.000000,712.000000,144.000000,0.000000])has
muaps comb9+3
and 0 muaps_not_in_combination comb9
and super([012.000000,712.000000,144.000000,0.000000])has
no_other_muaps comb9+0
then
muaps(1,2,3)form_superposition.

Which fact would you like to query ('c.' to continue)
3 muaps_in_combination comb9...
5.1 Introduction

LeFever and DeLuca (1982) found that it was impossible to measure the accuracy of their decomposition program with real EMG signals in an absolute sense. They explain that the true occurrence times of all the MUAPs in an EMG signal are not known; therefore it is not possible to state absolutely when the decomposed MUAPs have been correctly identified. They overcame this problem by using two approaches to test their decomposition method. Firstly, simulated EMG data were generated and used to test their decomposition program. Simulated EMG data were used in the testing of their decomposition program because they had a priori knowledge about the MU composition of the simulated EMG signals. The accuracy with which their decomposition program classified the MUAPs in a simulated EMG signal was then evaluated. Secondly, an experienced clinician decomposed real EMG signals and the results compared with the results of their decomposition program. The combined results of these two approaches were then taken as an indication of the accuracy of their decomposition procedure.

It was decided to use the same approach to test the accuracy of the new decomposition program. This chapter describes the different types of EMG data used to test the new decomposition program, the results of the tests carried out on simulated EMG data and the results of the tests carried out on real EMG data. All EMG data used in the testing of the decomposition program was classed into three main groups according to the amount of MUAP activity present in a signal.

- EMG data recorded at weak force level.
- EMG data recorded at medium force level.
- EMG data recorded at high force level.
It should be noted that the use of the words weak, medium and high all refer to fairly low percentages of a person's maximum voluntary contraction (0 - 20%). The amount of MUAP activity in an EMG signal was calculated by finding the root mean square (RMS) value of the normalised EMG data. The threshold levels arbitrarily chosen for classifying EMG data into the three groups are shown below.

<table>
<thead>
<tr>
<th>Group</th>
<th>RMS value</th>
</tr>
</thead>
<tbody>
<tr>
<td>weak force level</td>
<td>&lt; 4.0</td>
</tr>
<tr>
<td>medium force level</td>
<td>&gt; 4.0 &amp; &lt; 6.0</td>
</tr>
<tr>
<td>high force level</td>
<td>&gt; 6.0</td>
</tr>
</tbody>
</table>

The groups were also sub-divided into EMG data with high, medium and low signal-to-noise ratios (SNRs). The equation used to calculate the signal-to-noise ratio is given below.

\[
\text{SNR} = 10 \times \log_{10} \left( \frac{V_s}{V_n} \right) \text{ db} \tag{5.1}
\]

The voltages \( V_s \) and \( V_n \) represent the root mean square values of the signal and noise respectively. \( V_s \) was calculated by finding the root mean square voltage of the section of the EMG signal that contains the maximum amplitude. \( V_n \) was calculated by finding the root mean square voltage of the section of the EMG signal that contains the minimum amplitude. The threshold levels arbitrarily chosen for classifying EMG data into the three sub-groups are shown below.

<table>
<thead>
<tr>
<th>Group</th>
<th>SNR</th>
</tr>
</thead>
<tbody>
<tr>
<td>low SNR</td>
<td>&lt; 8.0 db</td>
</tr>
<tr>
<td>medium SNR</td>
<td>&gt; 8.0 &amp; &lt; 10.0 db</td>
</tr>
<tr>
<td>high SNR</td>
<td>&gt; 10.0 db</td>
</tr>
</tbody>
</table>

The number of polyphasic waveforms in an EMG signal was also noted because the existence of polyphasic waveforms increased the complexity of the automatic MUAP classification.
The results of the tests carried out on simulated and real EMG data are described using three case studies each. The three case studies on simulated EMG data show the accuracy of the decomposition program by comparing the results of the MUAP classifications with the actual MUAP information that was used to form the simulated EMG signals. The three case studies on real EMG data show the accuracy of the automatic MUAP classification by comparing the results with measurements made by an experienced clinician. The case studies on real EMG data also describe the intermediate results from the decomposition program to highlight the effectiveness of all sections of the work under different EMG recording conditions.

The new decomposition program was run on a DELL system 316SX personal computer (386SX machine). The specification of the computer is given below:

- CPU speed : 16MHz
- Base memory : 640KBytes
- Display : EGA/VGA
- Math coprocessor : 80387SX

5.2 Clinical EMG measurements

The new decomposition method was tested with EMG signals recorded by three different methods. The three different types of EMG signals are:

- Real EMG data recorded with needle electrodes.
- Real EMG data recorded with surface electrodes.
- Simulated EMG data.

5.2.1 Real needle EMG data

Needles - Monopolar (or single concentric) needle electrodes (see Fig.[5.1]) are used to record EMG data. The monopolar configuration contains one insulated wire in the cannula. The tip of the wire is bared and acts as a detection surface (see Fig.[5.2]). The wire core is commonly made from platinum and the cannula made from stainless steel. The tip angle of the electrode is the Buchtal standard 15°. The needle length can range from 15 to 125mm and the diameter from 0.306 to 0.65mm.
Fig[5.1]. A concentric needle electrode used in clinical practice.
Fig[5.2]. A schematic diagram of a needle electrode.
Clinical practice - The clinician inserts the needle electrode into the muscle of interest and asks the patient to relax the muscle. The needle is moved slightly and any signs of spontaneous electrical activity checked. The patient is then asked to perform a weak contraction of the muscle. The clinician slightly moves the needle until some MU activity is found. With a weak contraction the clinician can see individual MUAP trains in the EMG signal. Triggering levels are set on the recording equipment and the EMG data captured. The needle is then replaced in a different part of the muscle and the procedure repeated. The needle is re-inserted several times until a significant number of MUs have been captured.

Finally, the needle is re-inserted into the muscle and the patient is asked to perform a strong contraction of the muscle. The EMG signal recorded describes its macroscopic characteristics. A typical EMG signal recorded during a weak muscular contraction is shown in Fig.[5.3].

![EMG Signal](image)

**Fig.[5.3].** An EMG signal recorded at a weak force level.

5.2.2 Real surface EMG data

Surface electrodes were used to record real EMG signals because it is quick to collect data using this method and it is painless for the patient. The main problem with EMG data recorded with surface electrodes is that the EMG signals contain a large
number of MUAPs and the superposition effect of many MUAP trains cause the individual MUAP shapes to be lost. This problem has been overcome to some extent by Bhullar et al. (1990) where a new surface electrode has been designed to probe a much smaller area of muscle than a conventional surface electrode. Fig.[5.4] shows a schematic diagram of the new electrode configuration.

![Fig. 5.4. A schematic diagram of the new electrode configuration.](image)

The new electrode reduces the number of overlapping MUAP trains recorded at a given level of muscular contraction and makes it simpler to identify individual MUAP waveform shapes. The small surface area of the electrode plates, the small physical size and the concentric arrangement produce the effect of recording signals mainly from fibres near to the axis of the electrode and thereby make the electrode much more selective. The concentric ring instead of the normal passive electrode configuration also obviates the problem of electrode alignment relative to the direction of the muscle fibres. Examples of traces recorded with a conventional surface electrode and the new electrode from the first dorsal interoseous muscle at 20% maximum voluntary contraction are shown in Fig.[5.5]. It can be seen that MUAP trains are clearly identifiable in the EMG signal recorded with the new electrode.
The new surface electrode was used to record many EMG signals at low force levels and enabled the new EMG decomposition method to be quickly tested. One of the problems with surface EMG data is that the MUAPs from different MUs are generally of similar size and shape in comparison with EMG signals recorded using needle electrodes (Miller and Harrison, 1974). This is because the surface electrode,
unlike the needle electrode, is not surrounded by muscle fibres. Each MU recorded is
at a similar position relative to the surface electrode. Therefore, the number of MUAP
trains that could be recorded in a signal was restricted to one or two.

Clinical practice - The clinician places the surface electrode over the muscle of
interest. The patient is then asked to perform a weak contraction of the muscle. Using
the new electrode design the clinician can see individual MUAP trains in the EMG
signal. Triggering levels are set on the recording equipment as with the needle
electrode and the EMG data captured.

5.2.3 Simulated EMG data

Simulated EMG data was formed using different combinations of up to twenty
basic MUAP waveforms. The twenty MUAP waveforms varied in shape, relating to
normal and diseased waveforms that might be encountered in a clinical examination.
Trains of the basic MUAP waveforms were superimposed on one another to form a
simulated EMG signal. The mean firing period and standard deviation (of firing period
variability) of a MUAP train was randomly calculated (within limits) and the firing
period distribution of a train was made gaussian. The first MUAP waveform in a train
was found by contaminating the basic MUAP shape being used by white noise. The
contaminated MUAP was then used as the basic MUAP shape. The shape of the next
MUAP in the train was found by contaminating the new basic MUAP shape by white
noise. This procedure was then repeated to form all the MUAP shapes in the train.
This approach simulates the real situation when MUAPs gradually change in shape
over time due to movements of the recording electrode relative to the active MU (see
Fig.[5.6]).

Fig.[5.7] shows a simulated EMG signal containing three basic MUAP waveforms.
General background activity was formed and superimposed onto the simulated EMG
signal to produce a more realistic signal. The simulated background activity represents
wide band noise that is normally recorded and baseline wander in the signal due to
electrode movement. The background activity was calculated using the formula below.

\[
data_i = data_{i-1} + \text{random\_value} \ldots . . . . . . . . . . \quad (5.2)
\]
Fig.[5.6]. A simulated MUAP train.

Fig.[5.7]. A simulated EMG signal containing three MUAP trains and no noise.

Fig.[5.8]. A simulated EMG signal containing three MUAP trains and noise.
where data\(_i = 0 \) when \( i = 0 \) and data\(_i \) represents the \( i^{th} \) element in the background activity signal. The random_value was constrained to reduce the amount of noise present in the signal. Fig.\[5.8\] shows a simulated EMG signal containing the same three MUAP trains as in Fig.\[5.7\] superimposed with the background activity.

5.3 Results of tests carried out on simulated EMG data

Simulated EMG data were used in the testing of the new decomposition program because \( a \ priori \) knowledge was available about the MU composition of a simulated EMG signal. The accuracy with which the new decomposition program classifies the MUAPs in a simulated EMG signal could therefore be evaluated. The results of three tests carried out on simulated EMG signals are shown in this section as three case studies. The three tests were part of a large number of tests carried out on the decomposition program. The three simulated EMG signals contain four, five and six MUs respectively. The new decomposition program could not be tested on simulated EMG signals containing more MUs because of the limitations of the hardware used to run the decomposition program. The results summarise the findings from all the tests carried out on simulated EMG signals.

5.3.1 Case study [S1]

The simulated EMG signal used in this test contains four MUs. The EMG signal is shown in Fig.\[5.9\] along with the four basic MUAP waveforms used to form the signal. The specification of the MU information used to form the simulated EMG signal is given in Table\[5.1\]. A wandering baseline was incorporated into the simulated EMG signal to test the effectiveness of the filtering stages of the program. The simulated EMG signal contains twenty eight non-overlapping MUAPs and six overlapping MUAPs. The simulated signal represents an EMG signal recorded with a needle electrode at a medium force level. The simulated EMG signal has a medium SNR. The length of the simulated data is 800 msecs and is sampled at 10kHz.

The results of the classification of non-overlapping MUAPs are shown in Fig.\[5.10\]. The top section of the results shows the simulated EMG signal with labels, corresponding to the positions where the MUAPs from the different MUs are located.
The simulated EMG signal

The MUAP waveforms

Fig.[5.9]. The simulated EMG signal with the basic MUAP waveforms used to form the signal.
Table 5.1. The specification of the MU information used to form the simulated EMG signal.

<table>
<thead>
<tr>
<th></th>
<th>measurements</th>
</tr>
</thead>
<tbody>
<tr>
<td>MU found</td>
<td>4</td>
</tr>
<tr>
<td>MUAPs / MU found</td>
<td>11 7 8 9</td>
</tr>
<tr>
<td>Average duration of MUAPs / MU (ms)</td>
<td>5.3 3.7 2.9 3.1</td>
</tr>
<tr>
<td>Average pk. to pk. amplitude of MUAPs / MU (uv)</td>
<td>446 641 557 724</td>
</tr>
<tr>
<td>Mean firing period of MUs (ms)</td>
<td>72.1 99.8 95.0 78.7</td>
</tr>
<tr>
<td>Standard deviation of MU periods (ms)</td>
<td>5.1 6.1 8.4 6.7</td>
</tr>
</tbody>
</table>
Fig.[5.10]. The results of the classification of non-overlapping MUAPs.
Below, are pictures of the averaged MUAP waveforms from the different MUs classified and statistical information describing the size of the average MUAPs, the number of MUAPs found and the MU firing times. The decomposition program correctly classified all the non-overlapping MUAPs in the simulated EMG signal into four MU groups.

An update of the results after the classification of overlapping MUAPs is shown in Fig.[5.11]. All but one of the overlapping MUAPs have been correctly decomposed. Table[5.2] highlights the differences between the measurements of the MU information used to form the simulated EMG signal and the results of the MUAP classification. The average percentage errors between the measurements for the peak to peak amplitude, mean firing period and standard deviation measurements are less than five percent. The average percentage error between MUAP duration measurements is less than fifteen percent. The new decomposition method took 12 seconds to classify the non-overlapping MUAPs in the EMG signal and an additional 49 seconds to classify the superimposed waveforms containing overlapping MUAPs.

5.3.2 Case study [S2]

The simulated EMG signal used in this test contains five MUs. The EMG signal is shown in Fig.[5.12] along with the five basic MUAP waveforms used to form the signal. The specification of the MU information used to form the simulated EMG signal is given in Table[5.3]. The simulated EMG signal contains thirty two non-overlapping MUAPs and twelve overlapping MUAPs. The simulated signal represents an EMG signal recorded with a needle electrode at a medium force level. The simulated EMG signal has a low SNR. The length of the simulated data is 800 msecs and is sampled at 10kHz.

The results of the classification of non-overlapping MUAPs are shown in Fig.[5.13]. The top section of the results shows the simulated EMG signal with labels, corresponding to the positions where the MUAPs from the different MUs are located. Below, are pictures of the averaged MUAP waveforms from the different MUs classified and statistical information describing the size of the average MUAPs, the
Fig.[5.11]. An update of the results after the classification of all MUAPs.
<table>
<thead>
<tr>
<th></th>
<th>measurements</th>
<th>% error in results</th>
</tr>
</thead>
<tbody>
<tr>
<td><strong>MUs found</strong></td>
<td>4 4</td>
<td>0</td>
</tr>
<tr>
<td><strong>MUAPs / MU found</strong></td>
<td>11 10 7 7 8 8 9 9</td>
<td>3</td>
</tr>
<tr>
<td><strong>Average duration of MUAPs / MU (ms)</strong></td>
<td>5.3 5.4 3.7 4.3 2.9 3.6 3.1 3.7</td>
<td>13</td>
</tr>
<tr>
<td><strong>Average pk. to pk. amplitude of MUAPs / MU (uv)</strong></td>
<td>446 462 641 673 557 526 724 705</td>
<td>4</td>
</tr>
<tr>
<td><strong>mean firing period of MUs (ms)</strong></td>
<td>72.1 99.8 95.0 78.7</td>
<td>3</td>
</tr>
<tr>
<td></td>
<td>70.3 101.5 93.9 80.9</td>
<td></td>
</tr>
<tr>
<td><strong>standard deviation of MU periods (ms)</strong></td>
<td>5.1 5.4 6.1 6.2 8.4 8.1 6.7 6.4</td>
<td>4</td>
</tr>
</tbody>
</table>

- MU specification values shown in *italic* type
- results from automatic MUAP classification shown in **bold** type

**Table[5.2].** Comparison between the MU specification used to form the simulated EMG signal and the results of the automatic MUAP classification.
The simulated EMG signal

Fig. [5.12]. The simulated EMG signal with the basic MUAP waveforms used to form the signal.
Table 5.3. The specification of the MU information used to form the simulated EMG signal.

<table>
<thead>
<tr>
<th></th>
<th>measurements</th>
</tr>
</thead>
<tbody>
<tr>
<td><strong>MUs found</strong></td>
<td>5</td>
</tr>
<tr>
<td><strong>MUAPs / MU found</strong></td>
<td>7 9 11 10 9</td>
</tr>
<tr>
<td><strong>Average duration of MUAPs / MU (ms)</strong></td>
<td>5.3 2.9 3.7 3.1 5.1</td>
</tr>
<tr>
<td><strong>Average pk. to pk. amplitude of MUAPs / MU (uv)</strong></td>
<td>454 568 652 738 323</td>
</tr>
<tr>
<td><strong>mean firing period of MUs (ms)</strong></td>
<td>117.0 89.4 70.4 77.8 85.7</td>
</tr>
<tr>
<td><strong>standard deviation of MU periods (ms)</strong></td>
<td>5.1 6.1 8.4 7.6 6.7</td>
</tr>
</tbody>
</table>
Fig.[5.13]. The results of the classification of non-overlapping MUAPs.
number of MUAPs found and the MU firing times. The decomposition program correctly classified all the non-overlapping MUAPs in the simulated EMG signal into five MU groups.

An update of the results after the classification of overlapping MUAPs is shown in Fig.[5.14]. All overlapping MUAPs have been correctly decomposed. Table[5.4] highlights the differences between the measurements of the MU information used to form the simulated EMG signal and the results of the MUAP classification. The average percentage errors between the measurements for the peak to peak amplitude, mean firing period and standard deviation measurements are less than five percent. The average percentage error between MUAP duration measurements is less than fifteen percent. The new decomposition method took 13 seconds to classify the non-overlapping MUAPs in the EMG signal and an additional 159 seconds to classify the superimposed waveforms containing overlapping MUAPs.

5.3.3 Case study [S3]

The simulated EMG signal used in this test contains six MUs. The EMG signal is shown in Fig.[5.15] along with the six basic MUAP waveforms used to form the signal. The specification of the MU information used to form the simulated EMG signal is given in Table[5.5]. The simulated EMG signal contains thirty five non-overlapping MUAPs and fifteen overlapping MUAPs. The simulated signal represents an EMG signal recorded with a needle electrode at a high force level. The simulated EMG signal has a medium SNR. The length of the simulated data is 760 msecs and is sampled at 10kHz.

The results of the classification of non-overlapping MUAPs are shown in Fig.[5.16]. The top section of the results shows the simulated EMG signal with labels, corresponding to the positions where the MUAPs from the different MUs are located. Below, are pictures of the averaged MUAP waveforms from the different MUs classified and statistical information describing the size of the average MUAPs, the number of MUAPs found and the MU firing times. The decomposition program correctly classified all the non-overlapping MUAPs in the simulated EMG signal into six MU groups.
Fig.[5.14]. An update of the results after the classification of all MUAPs.
Table 5.4. Comparison between the MU specification used to form the simulated EMG signal and the results of the automatic MUAP classification.

<table>
<thead>
<tr>
<th></th>
<th>Measurements</th>
<th>% Error in Results</th>
</tr>
</thead>
<tbody>
<tr>
<td><strong>MUs found</strong></td>
<td>5 5</td>
<td>0</td>
</tr>
<tr>
<td><strong>MUAPs / MU found</strong></td>
<td>7 7 9 9 11 11 10 10 9 9</td>
<td>0</td>
</tr>
<tr>
<td><strong>Average duration of MUAPs / MU (ms)</strong></td>
<td>5.3 2.9 3.7 3.1 5.1</td>
<td>11</td>
</tr>
<tr>
<td></td>
<td>6.1 3.7 4.4 3.2 5.4</td>
<td></td>
</tr>
<tr>
<td><strong>Average pk. to pk. amplitude of MUAPs / MU (uv)</strong></td>
<td>454 568 652 738 323</td>
<td>4</td>
</tr>
<tr>
<td></td>
<td>460 529 674 707 339</td>
<td></td>
</tr>
<tr>
<td><strong>Mean firing period of MUs (ms)</strong></td>
<td>117.0 89.4 70.4 77.8 85.7</td>
<td>2</td>
</tr>
<tr>
<td></td>
<td>115.7 87.2 72.7 79.5 83.2</td>
<td></td>
</tr>
<tr>
<td><strong>Standard deviation of MU periods (ms)</strong></td>
<td>5.1 6.1 8.4 7.6 6.7</td>
<td>4</td>
</tr>
<tr>
<td></td>
<td>5.4 6.2 8.1 7.9 6.4</td>
<td></td>
</tr>
</tbody>
</table>

- MU specification values shown in *italic* type
- Results from automatic MUAP classification shown in **bold** type
The simulated EMG signal

Fig. [5.15]. The simulated EMG signal with the basic MUAP waveforms used to form the signal.
<table>
<thead>
<tr>
<th></th>
<th>measurements</th>
</tr>
</thead>
<tbody>
<tr>
<td>MUs found</td>
<td>6</td>
</tr>
<tr>
<td>MUAPs / MU found</td>
<td>11 8 7 8 9 9</td>
</tr>
<tr>
<td>Average duration of MUAPs / MU (ms)</td>
<td>3.7 4.4 5.3 2.9 3.1 5.1</td>
</tr>
<tr>
<td>Average pk. to pk. amplitude of MUAPs / MU (uv)</td>
<td>829 481 577 721 937 410</td>
</tr>
<tr>
<td>mean firing period of MUs (ms)</td>
<td>68.3 94.0 114.0 86.1 77.0 84.1</td>
</tr>
<tr>
<td>standard deviation of MU periods (ms)</td>
<td>7.2 5.1 5.5 5.6 6.7 5.8</td>
</tr>
</tbody>
</table>

Table[5.5]. The specification of the MU information used to form the simulated EMG signal.
Fig[5.16]. The results of the classification of non-overlapping MUAPs.
An update of the results after the classification of overlapping MUAPs is shown in Fig.[5.17]. All but four of the overlapping MUAPs have been correctly decomposed. Table[5.6] highlights the differences between the measurements of the MU information used to form the simulated EMG signal and the results of the MUAP classification. The average percentage errors between the measurements for the peak to peak amplitude and mean firing period measurements are less than five percent. The average percentage errors between MUAP duration and standard deviation measurements are less than fifteen percent. The new decomposition method took 13 seconds to classify the non-overlapping MUAPs in the EMG signal and an additional 101 seconds to classify the superimposed waveforms containing overlapping MUAPs.

5.4 Results of tests carried out on real EMG data

The accuracy with which the decomposition program classifies MUAPs in real EMG data is tested by comparing the results of the automatic MUAP classification with the results of a MUAP classification performed visually by an experienced clinician. The doctor who performed the visual analysis of the real EMG data was Dr. Ponsford, who is the EMG specialist at the Leicester Royal Infirmary. The results of three tests carried out on real EMG signals are shown in this section as three case studies. The results summarise the findings from all the tests carried out on real EMG signals. The intermediate results from the decomposition program are also highlighted to show the effectiveness of all sections of the work under different EMG recording conditions. Each case study is divided into three sections. The sections are :-

- The EMG data specification.
- The results of the visual decomposition performed by an experienced clinician.
- An explanation of the results from the decomposition program.

The three EMG signals chosen for the case studies contain different levels of noise, so that the effectiveness of the MUAP data collection section in the decomposition program under different conditions can be highlighted. The EMG signals chosen, also fall into different groups relating to the amount of activity in an
Fig[5.17]. An update of the results after the classification of all MUAPs.
<table>
<thead>
<tr>
<th></th>
<th>measurements</th>
<th>% error in results</th>
</tr>
</thead>
<tbody>
<tr>
<td><strong>MUs found</strong></td>
<td>6 6</td>
<td>0</td>
</tr>
<tr>
<td><strong>MUAPs / MU found</strong></td>
<td><strong>11 10 8 8</strong></td>
<td><strong>6 6 0 4</strong></td>
</tr>
<tr>
<td><strong>Average duration of</strong></td>
<td><strong>3.7 4.4 5.3</strong></td>
<td><strong>3.1 5.1 12</strong></td>
</tr>
<tr>
<td><strong>MUAPs / MU (ms)</strong></td>
<td><strong>4.5 5.0 5.6</strong></td>
<td><strong>3.4 5.4 12</strong></td>
</tr>
<tr>
<td><strong>Average pk. to pk.</strong></td>
<td><strong>829 481 577</strong></td>
<td><strong>937 410 4</strong></td>
</tr>
<tr>
<td><strong>amplitude of MUAPs / MU</strong></td>
<td><strong>854 499 583</strong></td>
<td><strong>896 428 4</strong></td>
</tr>
<tr>
<td><strong>(uv)</strong></td>
<td></td>
<td></td>
</tr>
<tr>
<td><strong>mean firing period of</strong></td>
<td><strong>68.3 94.0 114.0</strong></td>
<td><strong>77.0 84.1 4</strong></td>
</tr>
<tr>
<td><strong>MUs (ms)</strong></td>
<td><strong>58.5 97.0 115.7</strong></td>
<td><strong>85.4 83.2 4</strong></td>
</tr>
<tr>
<td><strong>standard deviation of</strong></td>
<td><strong>7.2 5.1 5.5</strong></td>
<td><strong>6.7 5.8 10</strong></td>
</tr>
<tr>
<td><strong>MU periods (ms)</strong></td>
<td><strong>12.3 5.3 5.4</strong></td>
<td><strong>6.9 6.4 10</strong></td>
</tr>
</tbody>
</table>

- MU specification values shown in *italic* type
- results from automatic MUAP classification shown in **bold** type

Table[5.6]. Comparison between the MU specification used to form the simulated EMG signal and the results of the automatic MUAP classification.
EMG signal. Each EMG signal contains a mixture of simple bi or triphasic waveforms and polyphasic waveforms. The variation in the amount and complexity of MUAP activity in the three EMG signals enables the effectiveness of the MUAP classification section in the decomposition program to be highlighted.

5.4.1 Case Study [R1]

The real EMG signal used in this case study is shown in Fig.[5.18].

Background Information:

Data set: Filename - med_rb22.msr; Muscle - right biceps; Recording device - concentric needle electrode; Force level - weak; SNR - high;

Data specification: Sampling frequency - 10KHz; Length of data - 1.26 secs;

Results from the visual decomposition:

The doctor observed two active motor units in the EMG signal and noted that four waveforms contained overlapping MUAPs and thirteen waveforms were non-overlapping MUAPs. The doctor based her decisions on the different shapes of the MUAPs that she found in the EMG signal. Information on the firing times of the MUs was not considered. Table[5.7] displays the measurements made by the doctor. The table shows the positions of the MUAPs in the signal, the maximum peak to peak amplitude of the MUAPs and the durations of the MUAPs. The table also states the MU group of each MUAP and whether the waveforms classified are non-overlapping or overlapping MUAPs.

Results from the decomposition program:

The high pass and low pass filtering of the EMG signal shown in Fig.[5.18] is not a very important criteria in this case, because the SNR is high and there is no baseline wander in the signal. The segmentation of the signal into areas of activity and inactivity is difficult because there are very small areas of activity in the signal relative to the baseline. Fig.[5.19] shows the results after the MUAP data collection section of the decomposition program. Twenty one active segments were found. (Each active segment is numbered to highlight the effects of the cluster analysis stage of the
Fig[5.18]. The raw EMG signal.

Fig[5.19]. The EMG signal after the MUAP data collection section.
<table>
<thead>
<tr>
<th>MUAPs</th>
<th>position (secs)</th>
<th>duration (msecs)</th>
<th>pk. to pk. amplitude (uv)</th>
<th>MU group</th>
</tr>
</thead>
<tbody>
<tr>
<td>1</td>
<td>0.0434</td>
<td>19.7</td>
<td>956</td>
<td>overlapping</td>
</tr>
<tr>
<td>2</td>
<td>0.1513</td>
<td>9.0</td>
<td>122</td>
<td>1</td>
</tr>
<tr>
<td>3</td>
<td>0.2006</td>
<td>13.1</td>
<td>983</td>
<td>2</td>
</tr>
<tr>
<td>4</td>
<td>0.2448</td>
<td>11.2</td>
<td>135</td>
<td>1</td>
</tr>
<tr>
<td>5</td>
<td>0.3192</td>
<td>21.2</td>
<td>965</td>
<td>overlapping</td>
</tr>
<tr>
<td>6</td>
<td>0.4195</td>
<td>8.8</td>
<td>124</td>
<td>1</td>
</tr>
<tr>
<td>7</td>
<td>0.4549</td>
<td>15.6</td>
<td>993</td>
<td>2</td>
</tr>
<tr>
<td>8</td>
<td>0.5094</td>
<td>12.0</td>
<td>130</td>
<td>1</td>
</tr>
<tr>
<td>9</td>
<td>0.5949</td>
<td>20.8</td>
<td>929</td>
<td>overlapping</td>
</tr>
<tr>
<td>10</td>
<td>0.7148</td>
<td>16.6</td>
<td>852</td>
<td>2</td>
</tr>
<tr>
<td>11</td>
<td>0.8063</td>
<td>11.3</td>
<td>136</td>
<td>1</td>
</tr>
<tr>
<td>12</td>
<td>0.8672</td>
<td>13.0</td>
<td>882</td>
<td>2</td>
</tr>
<tr>
<td>13</td>
<td>0.9024</td>
<td>10.1</td>
<td>132</td>
<td>1</td>
</tr>
<tr>
<td>14</td>
<td>0.9944</td>
<td>20.9</td>
<td>964</td>
<td>overlapping</td>
</tr>
<tr>
<td>15</td>
<td>1.0989</td>
<td>10.8</td>
<td>132</td>
<td>1</td>
</tr>
<tr>
<td>16</td>
<td>1.1422</td>
<td>14.2</td>
<td>899</td>
<td>2</td>
</tr>
<tr>
<td>17</td>
<td>1.2066</td>
<td>8.4</td>
<td>134</td>
<td>1</td>
</tr>
</tbody>
</table>

Table[5.7]. Measurements and observations made by the doctor.
program later). All active segments were described by eight features each and the correlation between features found. Eight uncorrelated weighted features were formed from the eight correlated features by using diagonal factor analysis. The non-zero weighted features are shown below.

<table>
<thead>
<tr>
<th>Feature</th>
<th>Weight</th>
</tr>
</thead>
<tbody>
<tr>
<td>max. pk. to pk. amplitude</td>
<td>1.00</td>
</tr>
<tr>
<td>duration</td>
<td>0.46</td>
</tr>
</tbody>
</table>

These uncorrelated weighted features were used to classify the active segments into MU groups. Only two weighted features were required to completely describe the active segment shapes. There was a high correlation between all the features describing an active segment.

The cluster analysis section of the decomposition program was then performed to classify the active segments (described by two weighted features each) into MU groups. The top section of Fig.[5.20] shows the network distance graph formed during the cluster analysis section of the program. The threshold level calculated, is labelled on the graph. The bottom section of Fig.[5.20] shows the results of the cluster analysis. Two large groups have been formed, with one active segment that is not in any group. Each of the two large groups were classed as a MU group. The active segments in the MU groups are classed as non-overlapping MUAPs from that MU. The active segment not in a group was classed as a superimposed waveform.

The average MUAP waveform of each MU group was then formed by finding the median average of the MUAPs. The average MUAP waveforms are used later in the decomposition program to decompose the superimposed waveform into its constituent MUAPs. The periods between MUAP firings within a MU were calculated and used to find the firing period variability within a MU.

Fig.[5.21] shows the results produced by the decomposition program for the clinician after the classification of the non-overlapping MUAPs. The top section of the results shows the EMG signal with labels, corresponding to the positions where the MUAPs from the two MUs classified, are located. The position of the superimposed waveform not classified at this stage is also marked (labelled s1). Below, are pictures
The groups of active segments are:

20 13 6 18 17 1 11 15 4 9 7 2 18 16 19 0 14 3 5 12

Fig.[5.20]. The network distance graph formed during the cluster analysis.
Fig[5.21]. The results of the classification of non-overlapping MUAPs.
of the average MUAPs from the two MUs classified and the statistical information describing the size of the two average MUAPs, the numbers of MUAPs found and the MU firing variability. Fig.[5.22] shows the overprinting of MUAPs from the same MU. It can be seen that the variation in the shapes of the MUAPs from MU2 are similar to that of the MUAPs from MU1. Fig.[5.23] emphasises this point. The graph shows the relative variation in the shapes of the MUAPs from the different MUs during the recording. Each point represents the euclidean distance between the vectors describing MUAPs from the same MU. Fig.[5.24] gives information on the firing statistics of the two MUs captured, by displaying the mean firing periods of the MUs and the standard deviations of firing period variability within a MU. The standard deviation of the firing period variability of MU2 is larger than MU1.

The superimposed waveform (s1) was then classified by the decomposition section of the program. The decomposition section uses the average MUAP waveforms formed in the MUAP classification section and information on the firing times of the non-overlapping MUAPs. Three MUAP combination candidates can form the superimposed waveform. MUAP1 only, MUAP2 only and a combination of MUAPs 1 and 2. The three main stages of the superimposed waveform decomposition are shown in Table [5.8].

<table>
<thead>
<tr>
<th>superimposed waveform</th>
<th>MUAP combination candidates after stage 1</th>
<th>MUAP combination candidates after stage 2</th>
<th>MUAP combination selected</th>
<th>certainty of results after stage 3</th>
</tr>
</thead>
<tbody>
<tr>
<td>s1</td>
<td>MUAP2, MUAP1 &amp; 2</td>
<td>MUAP2, MUAP1 &amp; 2</td>
<td>MUAP1 &amp; 2</td>
<td>0.45</td>
</tr>
</tbody>
</table>

Table[5.8]. The results from the intermediate stages of the decomposition of the superimposed waveform.

Column 1 shows the two MUAP combination candidates selected from stage 1 (combination reduction). MUAP1 only has been discarded as a MUAP combination candidate. Column 2 shows the same two MUAP combination candidates selected after stage 2 (optimisation). Both MUAP combination candidates were selected
Fig.[5.22]. The overprinting of MUAPs from the same MU.

Fig.[5.23]. The variation in MUAP shape during a recording.
Fig.[5.24]. The firing statistics of the MUs classified.

Fig[5.25]. An update of the results after the classification of all MUAPs.
because of their similarity in shape to the superimposed waveform. Column 3 shows that a combination of MUAPs 1 and 2 was selected after stage 3 (the expert system stage). Column 4 shows that the expert system made a decision with a certainty of 0.45 that MUAPs 1 and 2 formed the superimposed waveform. This conclusion was formed even when there was a large variability in the firing periods of one of the MUs. The expert system used the firing time information of the MUs to make a decision. The result of the decomposition of the superimposed waveform was used to update the firing statistics of the MUs.

Fig.[5.25] shows the results produced by the decomposition program for the clinician after the classification of both non-overlapping and overlapping MUAPs with an updated version of the MU information. Table[5.9] gives a list of the main measurements made during the decomposition program. The decomposition program took 14 seconds to classify the 20 non-overlapping MUAPs in the EMG signal and an additional 6 seconds to classify the superimposed waveform containing two overlapping MUAPs. Both the visual and automatic decomposition methods identified two MUs in the EMG signal. The automatic analysis found five more MUAPs in MU1 and four more MUAPs in MU2 because the program could decompose overlapping MUAPs. There was a 7% error between the average peak to peak amplitudes of the MUAPs measured by the automatic and visual decomposition methods. There was a 10% error between the average duration of the MUAPs measured by the automatic and visual decomposition methods.
<table>
<thead>
<tr>
<th>measurements</th>
<th>2</th>
<th>9</th>
</tr>
</thead>
<tbody>
<tr>
<td><strong>MUs found</strong></td>
<td>13</td>
<td>9</td>
</tr>
<tr>
<td>MUAPs / MU found</td>
<td><strong>Mean ± SD</strong></td>
<td>8.8 ± 0.3</td>
</tr>
<tr>
<td>Duration of MUAPs (ms)</td>
<td><strong>Mean ± SD</strong></td>
<td>132 ± 2</td>
</tr>
<tr>
<td>Peak to peak amplitude of MUAPs</td>
<td><strong>Mean ± SD</strong></td>
<td>95.2 ± 6.9</td>
</tr>
<tr>
<td>Firing period of MUs (ms)</td>
<td><strong>Mean ± SD</strong></td>
<td>95.2 ± 6.9</td>
</tr>
</tbody>
</table>

Table[5.9]. Main measurements of results from decomposition program after the classification of non-overlapping and overlapping MUAPs.
5.4.2 Case Study [R2]

The real EMG signal used in this case study is shown in Fig.[5.26].

**Background Information:**

**Data set:** Filename - med_fd10.msr; Muscle - unknown; Recording device - concentric needle electrode; Force level - high; SNR - low;

**Data specification:** Sampling frequency - 10KHz; Length of data - 669ms;

**Results of the visual decomposition:**

The doctor observed at least four possible active MUs in the EMG signal but found it difficult to make a definite judgement on the MUAP classification because of the large variability in the shape of the MUAPs. Twenty seven MUAPs were found in the EMG signal. The doctor stated that the variability in the MUAP shapes could be because of disease to the MUAPs and/or because the recording electrode was moving relative to the active muscle fibres. The doctor also recorded the fact that the background noise was fairly high. No MUAPs were classed into a MU group. Table[5.10] displays the measurements made by the doctor. The table shows the positions of the MUAPs in the signal, the maximum peak to peak amplitude of the MUAPs and the durations of the MUAPs. Column five indicates the doctor’s indecision in classifying the MUAPs into different MU groups.

**Results from the decomposition program:**

The EMG signal shown in Fig.[5.26] contains a low SNR. The EMG signal also has a wandering baseline. The high and low pass filtering stages of the decomposition program are therefore important. The results of the filtering stages of the decomposition program are shown in the top section of Fig.[5.27]. The baseline drift in the EMG signal has been eliminated. Even so, there is still a significant amount of background activity present in the signal and there are signs of very small MUAP activity in relation to the background noise. It is therefore difficult for the segmentation stage of the program to extract the small activity from the background noise to see if the activity is due to MU firings. The results after the MUAP data
Fig[5.26]. The raw EMG signal.

Fig[5.27]. The EMG signal after (a) the filtering stage and (b) the normalisation and segmentation stages.
<table>
<thead>
<tr>
<th>MUAPs</th>
<th>position (secs)</th>
<th>duration (msecs)</th>
<th>pk. to pk. amplitude (uv)</th>
<th>MU group</th>
</tr>
</thead>
<tbody>
<tr>
<td>1</td>
<td>0.0155</td>
<td>8.3</td>
<td>1687</td>
<td>?</td>
</tr>
<tr>
<td>2</td>
<td>0.0279</td>
<td>3.0</td>
<td>562</td>
<td>?</td>
</tr>
<tr>
<td>3</td>
<td>0.0622</td>
<td>6.0</td>
<td>1615</td>
<td>?</td>
</tr>
<tr>
<td>4</td>
<td>0.1021</td>
<td>3.7</td>
<td>595</td>
<td>?</td>
</tr>
<tr>
<td>5</td>
<td>0.1292</td>
<td>5.4</td>
<td>1554</td>
<td>?</td>
</tr>
<tr>
<td>6</td>
<td>0.1476</td>
<td>3.4</td>
<td>239</td>
<td>?</td>
</tr>
<tr>
<td>7</td>
<td>0.1624</td>
<td>6.9</td>
<td>1825</td>
<td>?</td>
</tr>
<tr>
<td>8</td>
<td>0.1734</td>
<td>3.4</td>
<td>573</td>
<td>?</td>
</tr>
<tr>
<td>9</td>
<td>0.2095</td>
<td>6.1</td>
<td>1597</td>
<td>?</td>
</tr>
<tr>
<td>10</td>
<td>0.2388</td>
<td>4.0</td>
<td>288</td>
<td>?</td>
</tr>
<tr>
<td>11</td>
<td>0.2556</td>
<td>4.4</td>
<td>158</td>
<td>?</td>
</tr>
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<td>12</td>
<td>0.2690</td>
<td>2.3</td>
<td>581</td>
<td>?</td>
</tr>
<tr>
<td>13</td>
<td>0.2775</td>
<td>4.4</td>
<td>1583</td>
<td>?</td>
</tr>
<tr>
<td>14</td>
<td>0.3102</td>
<td>6.7</td>
<td>1833</td>
<td>?</td>
</tr>
<tr>
<td>15</td>
<td>0.3233</td>
<td>2.4</td>
<td>208</td>
<td>?</td>
</tr>
<tr>
<td>16</td>
<td>0.3513</td>
<td>2.7</td>
<td>585</td>
<td>?</td>
</tr>
<tr>
<td>17</td>
<td>0.3572</td>
<td>5.1</td>
<td>1626</td>
<td>?</td>
</tr>
<tr>
<td>18</td>
<td>0.4269</td>
<td>6.1</td>
<td>1493</td>
<td>?</td>
</tr>
<tr>
<td>19</td>
<td>0.4589</td>
<td>6.3</td>
<td>1821</td>
<td>?</td>
</tr>
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<td>20</td>
<td>0.4897</td>
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<tr>
<td>22</td>
<td>0.5064</td>
<td>2.5</td>
<td>585</td>
<td>?</td>
</tr>
<tr>
<td>23</td>
<td>0.5755</td>
<td>6.5</td>
<td>1644</td>
<td>?</td>
</tr>
<tr>
<td>24</td>
<td>0.5847</td>
<td>2.7</td>
<td>585</td>
<td>?</td>
</tr>
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<td>25</td>
<td>0.6049</td>
<td>8.8</td>
<td>1783</td>
<td>?</td>
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<td>26</td>
<td>0.6475</td>
<td>4.6</td>
<td>1759</td>
<td>?</td>
</tr>
<tr>
<td>27</td>
<td>0.6534</td>
<td>2.2</td>
<td>585</td>
<td>?</td>
</tr>
</tbody>
</table>

Table[5.10]. Measurements and observations made by the doctor.
collection section of the decomposition program are shown in the bottom section of Fig.[5.27]. Twenty six active segments were found. (Each active segment is numbered to highlight the effects of the cluster analysis stage of the program later). All active segments were described by eight features each and the correlation between features found. Eight uncorrelated weighted features were formed from the eight correlated features by using diagonal factor analysis. The non-zero weighted features are shown below.

<table>
<thead>
<tr>
<th>Feature</th>
<th>Weight</th>
</tr>
</thead>
<tbody>
<tr>
<td>maximum peak to peak amplitude</td>
<td>1.00</td>
</tr>
<tr>
<td>total negative area</td>
<td>0.46</td>
</tr>
<tr>
<td>duration</td>
<td>0.40</td>
</tr>
</tbody>
</table>

One more feature was required to describe the active segment shapes. The amount of correlation between features was reduced.

The cluster analysis section of the decomposition program was then performed to classify the active segments (described by three weighted features each) into MU groups. The top section of Fig.[5.28] shows the network distance graph formed during the cluster analysis section of the program. The threshold level calculated, is labelled on the graph. The bottom section of Fig.[5.28] shows the results of the cluster analysis. Three large groups have been formed and one slightly smaller group formed. There is one active segment that is not in any group. Each of the three large groups were classed as a MU group containing MUAPs from the same MU. The slightly smaller group contained only four active segments and was not classed as a MU group because at least five active segments must exist in a group for a reliable decision to be made. Instead, they were classed as superimposed waveforms along with the active segment not in any group.

The average MUAP waveform of each MU group was then formed by finding the median average of the MUAPs. The average MUAP waveforms are used later in the decomposition program to decompose the superimposed waveforms into their constituent MUAPs. The periods between MUAP firings within a MU were calculated and used to find the firing period variability within a MU.
The active segment groups are:

25 22 20 14 10 7 1 3 13 5 18 9 4 11 8 15 21 19 24 2 16 0 6 17 12 23

Fig.[5.28]. The network distance graph formed during the cluster analysis.
Fig. [5.29] shows the results produced by the decomposition program for the clinician after the classification of the non-overlapping MUAPs. The top section of the results shows the EMG signal with labels, corresponding to the positions where the MUAPs from the three MUs classified are located. The positions of the active segments classed as superimposed waveforms not classified at this stage are also marked (s1 - s5). Below, are pictures of the average MUAP shapes from the three MUs classified and the statistical information describing the size of the average MUAPs, the numbers of MUAPs found and the MU firing times. Fig. [5.30] shows the overprinting of MUAPs from the same MU. The MUAP waveforms from the three MUs are shown along with the waveforms from the smaller group formed in the cluster analysis stage of the decomposition program. It can be seen that this fourth group contains waveforms that are similar in shape. The waveforms could be MUAPs from a fourth MU. The variation in the shapes of the MUAPs from the three MUs classified are similar. Fig. [5.31] emphasises this point. The graph shows how the shapes of the MUAPs from the three different MUs varied relative to each other during the recording. Each point represents the euclidean distance between the vectors describing MUAPs from the same MU. Fig. [5.32] gives information on the firing statistics of the MUs captured, by displaying the mean firing periods of the MUs and the standard deviations of firing period variability within a MU. The standard deviation of firing period variability for each MU is similar.

The superimposed waveforms (s1 - s5) were then classified by the decomposition section of the program. The decomposition section uses the average MUAP waveforms formed in the MUAP classification section and information on the firing times of the non-overlapping MUAPs. Seven MUAP combination candidates can form each superimposed waveform. There is also the possibility that each superimposed waveform does not contain overlapping MUAPs classified in the last stage of the program. The three main stages of the superimposed waveform decomposition are shown in Table [5.11].

Column 1 shows the MUAP combination candidates selected from stage 1 (combination reduction). Column 2 shows the MUAP combination candidates selected after stage 2 (optimisation). Column 3 shows the final MUAP combination selected
Fig.[5.29]. The results of the classification of non-overlapping MUAPs.
Fig.[5.30]. The overprinting of MUAPs from the same MU.
**Fig. [5.31].** The variation in MUAP shape during a recording.

**Fig. [5.32].** The firing statistics of the MUs captured.
<table>
<thead>
<tr>
<th>superimposed waveform</th>
<th>MUAP combination candidates after stage 1</th>
<th>MUAP combination candidates after stage 2</th>
<th>MUAP combination selected</th>
<th>certainty of results after stage 3</th>
</tr>
</thead>
<tbody>
<tr>
<td>s1</td>
<td>MUAP1, MUAP1&amp;3, MUAP1&amp;2&amp;3, MUAP2, MUAP2&amp;3</td>
<td>MUAP1</td>
<td>NONE</td>
<td>N/A</td>
</tr>
<tr>
<td>s2</td>
<td>MUAP1, MUAP1&amp;3, MUAP1&amp;2&amp;3, MUAP2, MUAP2, MUAP2&amp;3</td>
<td>MUAP1</td>
<td>NONE</td>
<td>N/A</td>
</tr>
<tr>
<td>s3</td>
<td>MUAP1, MUAP1&amp;3, MUAP1&amp;2&amp;3, MUAP2, MUAP2, MUAP2&amp;3</td>
<td>MUAP1</td>
<td>NONE</td>
<td>N/A</td>
</tr>
<tr>
<td>s4</td>
<td>MUAP1, MUAP1&amp;2, MUAP1&amp;2&amp;3, MUAP2, MUAP2, MUAP2&amp;3</td>
<td>MUAP1&amp;2</td>
<td>MUAP1&amp;2</td>
<td>1.00</td>
</tr>
<tr>
<td>s5</td>
<td>MUAP1, MUAP1&amp;3, MUAP1&amp;2&amp;3, MUAP2, MUAP2, MUAP2&amp;3</td>
<td>MUAP1</td>
<td>NONE</td>
<td>N/A</td>
</tr>
</tbody>
</table>

Table[5.11]. The results from the intermediate stages of the decomposition of the superimposed waveforms.
after stage 3 (the expert system stage). Column 4 shows the certainty with which the expert system makes a decision. The results of the decomposition stage of the program show that superimposed waveform s1 was decomposed into MUAPs 3 and 4. The expert system made its decision with total certainty (1.0). The expert system decided that the other superimposed waveforms were not formed through a combination of MUAPs classified earlier with total certainty. The number of possible MUAP combinations that could form each superimposed waveform was large in comparison with the previous case study. The results from the decomposition of the superimposed waveforms were used to update the firing statistics of the MUs.

Fig.[5.33] shows the results produced by the decomposition program for the clinician after the classification of non-overlapping and overlapping MUAPs with an updated version of the MU information. Table[5.12] gives a list of the main measurements made during the decomposition program. The decomposition program took 11 seconds to classify the 21 non-overlapping MUAPs from the three MUs and an additional 31 seconds to classify the superimposed waveform containing two overlapping MUAPs and to analyse the four other areas of activity classed as superimposed waveforms. The decomposition program definitely identified three MUs in the EMG signal. A fourth possible MU was also identified by the program. This result correlates with the observation made by the doctor that there were at least four active MUs in the EMG signal. The observation made by the doctor that there was a large variability between MUAPs is not backed up the decomposition program (see the overprinting of MUAPs from the same MU in Fig.[5.30]). A graph of the MUAP measurements made by the doctor and the MUAP measurements made by the decomposition program is shown in Fig.[5.34]. It can be seen that the MUAPs classified into MU groups by the decomposition program are similar in size to the MUAPs measured by the doctor.
Fig.[5.33]. An update of the results of the analysis after the decomposition of superimposed waveforms.
Table 5.12. Main measurements of results from decomposition program after the classification of non-overlapping and overlapping MUAPs.

<table>
<thead>
<tr>
<th>Measurements</th>
<th>MUs found</th>
<th>MUAPs / MU found</th>
<th>MUAPs / MU found</th>
<th>MUAPs / MU found</th>
</tr>
</thead>
<tbody>
<tr>
<td>MUs found</td>
<td>3</td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>MUAPs / MU found</td>
<td>9</td>
<td>9</td>
<td>5</td>
<td></td>
</tr>
<tr>
<td>Duration of MUAPs (ms) - Mean ± SD</td>
<td>3.8 ± 0.6</td>
<td>5.8 ± 1.2</td>
<td>7.5 ± 1.1</td>
<td></td>
</tr>
<tr>
<td>Peak to peak amplitude of MUAPs (μV) - Mean ± SD</td>
<td>580 ± 7</td>
<td>1483 ± 61</td>
<td>1913 ± 29</td>
<td></td>
</tr>
<tr>
<td>Firing period of MUs (ms) - Mean ± SD</td>
<td>77.1 ± 7.9</td>
<td>71.4 ± 5.2</td>
<td>147.0 ± 6.0</td>
<td></td>
</tr>
</tbody>
</table>
Fig.[5.34]. A graph showing the similarity between the MUAP measurements made by the clinician and the MUAP measurements made by the decomposition program.
5.4.3 Case Study [R3]

The real EMG signal used in this case study is shown in Fig.[5.35].

Background Information:

Data set: Filename - med_fd12.msr; Muscle - unknown; Recording device - concentric needle electrode; Force level - high; SNR - low;

Data specification: Sampling frequency - 10KHz; Length of data - 713ms;

Results of the visual decomposition:

The doctor did not attempt to classify the MUAPs in the EMG signal into MU groups because of the complexity of the signal but suggested there were at least four active MUs in the signal. The doctor identified thirty seven areas of MUAP activity in the EMG signal of which at least four were due to overlapping MUAPs. The doctor also observed large variability in the shapes of the MUAPs and a large amount of background noise. Table[5.13] displays the measurements made by the doctor. The table shows the positions of the MUAPs in the signal, the maximum peak to peak amplitude of the MUAPs and the durations of the MUAPs. Column five shows that the doctor could not classify the MUAPs into different MU groups.

Results from the decomposition program:

The EMG signal shown in Fig.[5.35] contains a low SNR. There is noise over a wide range of frequencies. Low frequency noise produces the wandering baseline in the EMG signal. Higher frequency noise produces the constant activity that exists near the baseline of the signal. The results of the filtering stages of the decomposition program are shown in the top section of Fig.[5.36]. The baseline drift in the EMG signal has been eliminated. Higher frequency noise that exists near the baseline of the signal cannot be eliminated because the frequency range of the noise is the same as the frequency range of the MUAP activity in the EMG signal. Therefore, the segmentation stage of the decomposition program is difficult because the program has to decide what is MUAP activity and what is background noise. The results after the MUAP data collection section of the decomposition program are shown in the bottom section.
Fig[5.35]. The raw EMG signal.

Fig[5.36]. The EMG signal after (a) the filtering stage and (b) the normalisation and segmentation stages.
<table>
<thead>
<tr>
<th>MUAPs</th>
<th>position (secs)</th>
<th>duration (msecs)</th>
<th>pk. to pk. amplitude (uv)</th>
<th>MU group</th>
</tr>
</thead>
<tbody>
<tr>
<td>1</td>
<td>0.0093</td>
<td>3.5</td>
<td>476</td>
<td>?</td>
</tr>
<tr>
<td>2</td>
<td>0.0190</td>
<td>7.5</td>
<td>352</td>
<td>?</td>
</tr>
<tr>
<td>3</td>
<td>0.0418</td>
<td>2.5</td>
<td>434</td>
<td>?</td>
</tr>
<tr>
<td>4</td>
<td>0.0578</td>
<td>14.0</td>
<td>1789</td>
<td>?</td>
</tr>
<tr>
<td>5</td>
<td>0.0808</td>
<td>2.8</td>
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<td>6</td>
<td>0.0969</td>
<td>6.5</td>
<td>358</td>
<td>?</td>
</tr>
<tr>
<td>7</td>
<td>0.1084</td>
<td>4.1</td>
<td>410</td>
<td>?</td>
</tr>
<tr>
<td>8</td>
<td>0.1324</td>
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<td>?</td>
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<td>0.1471</td>
<td>2.9</td>
<td>482</td>
<td>?</td>
</tr>
<tr>
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<td>0.1707</td>
<td>3.9</td>
<td>352</td>
<td>?</td>
</tr>
<tr>
<td>11</td>
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<td>421</td>
<td>?</td>
</tr>
<tr>
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<td>?</td>
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</tr>
<tr>
<td>17</td>
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<td>?</td>
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<tr>
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<td>0.3457</td>
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<td>1816</td>
<td>overlapping</td>
</tr>
<tr>
<td>20</td>
<td>0.3860</td>
<td>4.6</td>
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</tr>
<tr>
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<td>2.2</td>
<td>410</td>
<td>?</td>
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<td>?</td>
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<td>0.4497</td>
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<td>329</td>
<td>?</td>
</tr>
<tr>
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<td>0.4613</td>
<td>5.7</td>
<td>398</td>
<td>?</td>
</tr>
<tr>
<td>25</td>
<td>0.4875</td>
<td>13.7</td>
<td>1737</td>
<td>overlapping</td>
</tr>
<tr>
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<td>0.5223</td>
<td>8.7</td>
<td>530</td>
<td>overlapping</td>
</tr>
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<td>27</td>
<td>0.5572</td>
<td>4.7</td>
<td>477</td>
<td>?</td>
</tr>
<tr>
<td>28</td>
<td>0.5653</td>
<td>15.1</td>
<td>1648</td>
<td>?</td>
</tr>
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<td>29</td>
<td>0.5907</td>
<td>6.4</td>
<td>341</td>
<td>?</td>
</tr>
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<td>30</td>
<td>0.6066</td>
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<td>?</td>
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<td>31</td>
<td>0.6187</td>
<td>3.9</td>
<td>477</td>
<td>?</td>
</tr>
<tr>
<td>32</td>
<td>0.6283</td>
<td>10.2</td>
<td>1831</td>
<td>?</td>
</tr>
<tr>
<td>33</td>
<td>0.6435</td>
<td>3.7</td>
<td>298</td>
<td>?</td>
</tr>
<tr>
<td>34</td>
<td>0.6576</td>
<td>5.6</td>
<td>352</td>
<td>?</td>
</tr>
<tr>
<td>35</td>
<td>0.6660</td>
<td>4.0</td>
<td>423</td>
<td>?</td>
</tr>
<tr>
<td>36</td>
<td>0.6783</td>
<td>5.3</td>
<td>494</td>
<td>?</td>
</tr>
<tr>
<td>37</td>
<td>0.6964</td>
<td>6.5</td>
<td>1877</td>
<td>?</td>
</tr>
</tbody>
</table>

Table[5.13]. Measurements and observations made by the doctor.
of Fig.[5.36]. Forty two active segments were found. (Each active segment is numbered to highlight the effects of the cluster analysis stage of the program later). All active segments were described by eight features each and the correlation between features found. Eight uncorrelated weighted features were formed from the eight correlated features by using diagonal factor analysis. The non-zero weighted features are shown below.

<table>
<thead>
<tr>
<th>Feature</th>
<th>Weight</th>
</tr>
</thead>
<tbody>
<tr>
<td>maximum peak to peak amplitude</td>
<td>1.00</td>
</tr>
<tr>
<td>duration</td>
<td>0.64</td>
</tr>
<tr>
<td>maximum negative slope</td>
<td>0.47</td>
</tr>
<tr>
<td>maximum negative peak amplitude</td>
<td>0.36</td>
</tr>
</tbody>
</table>

The weighted features were used to classify the active segments into MU groups. The amount of correlation between features describing the active segments was less than in the previous two case studies, which suggests that there is more variability in the shapes of the MUAPs in the EMG signal.

The cluster analysis section of the decomposition program was then performed to classify the active segments (described by four weighted features each) into MU groups. The top section of Fig.[5.37] shows the network distance graph formed during the cluster analysis section of the program. The threshold level calculated, is labelled on the graph. The bottom section of Fig.[5.38] shows the results of the cluster analysis. Four large groups have been formed, with four active segments that are not in any group. Each of the four large groups were classed as a MU group. The active segments in the MU groups were classed as non-overlapping MUAPs from that MU. The active segments not in a group were classed as superimposed waveforms.

The average MUAP waveform of each MU group was then formed by finding the median average of the MUAPs. The average MUAP waveforms are used later in the decomposition program to decompose the superimposed waveforms into their constituent MUAPs. The periods between MUAP firings within a MU were calculated and used to find the firing period variability within a MU.
The active segment groups are:

41 36 11 7 3 19 15 26 30 22 25 4 34 40 16 0 12 0 29 10 2 39 6 10 33 28 14 24 21 23 30 32 5 1 27 28 13 9 17 37 31 36

Fig.[5.37]. The network distance graph formed during the cluster analysis.
Fig.[5.38] shows the results produced by the decomposition program for the clinician after the classification of the non-overlapping MUAPs. The top section of the results shows the EMG signal with labels, corresponding to the positions where the MUAPs from the four MUs classified, are located. The positions of the active segments classed as superimposed waveforms not classified at this stage are also marked (s1 - s4). Below, are pictures of the average MUAPs from the four MUs classified and the statistical information describing the size of the four average MUAPs, the numbers of MUAPs found and the MU firing variability. Fig.[5.39] shows the overprinting of MUAPs from the same MU. It can be seen that the variation in shapes of MUAPs from MU1 is much larger than for the other MU groups. It should also be noted that the average waveform formed for MU1 (using median averaging) has lost some of the polyphasic information that can be seen in the overprinting of the MUAPs. Fig.[5.40] shows the relative variation in shape of MUAPs from the different MUs during the recording and emphasises the large variability in shape between MUAPs from MU1 in comparison to the MUAPs from the other MUs. Each point represents the euclidean distance between the vectors describing MUAPs from the same MU. Fig.[5.41] gives information on the firing statistics of the MUs captured, by displaying the mean firing periods of the MUs and the standard deviations of firing period variability within a MU. The standard deviation of firing period variability for each MU is similar.

The superimposed waveforms (s1 - s4) were then classified by the decomposition section of the program. The decomposition section uses the average MUAP waveforms formed in the MUAP classification section and information on the firing times of the non-overlapping MUAPs. Fourteen MUAP combination candidates can form each superimposed waveform and there is the possibility that each superimposed waveform does not contain overlapping MUAPs classified in the last stage of the program. The three main stages of the superimposed waveform decomposition are shown in Table [5.14].

Column 1 shows the MUAP combination candidates selected from stage 1 (combination reduction). Column 2 shows the MUAP combination candidates selected after stage 2 (optimisation). Column 3 shows the final MUAP combination selected
Fig.[5.38]. The results of the classification of non-overlapping MUAPs.
Fig.[5.39]. The overprinting of MUAPs from the same MU.

This waveform could be MUAP2 that is linked to MUAP1.
Fig.[5.40]. The variation in MUAP shape during a recording.

Fig.[5.41]. The firing statistics of the MUs captured.
<table>
<thead>
<tr>
<th>superimposed waveform</th>
<th>MUAP combination candidates after stage 1</th>
<th>MUAP combination candidates after stage 2</th>
<th>MUAP combination selected</th>
<th>certainty of results after stage 3</th>
</tr>
</thead>
<tbody>
<tr>
<td>s1</td>
<td>MUAP1, MUAP1&amp;2, MUAP1&amp;3, MUAP1&amp;2&amp;3,</td>
<td>MUAP1&amp;2, MUAP1&amp;2&amp;4, MUAP1&amp;2&amp;3</td>
<td>MUAP1&amp;2</td>
<td>1.00</td>
</tr>
<tr>
<td></td>
<td>MUAP1&amp;2&amp;4, MUAP2&amp;3&amp;4, MUAP3, MUAP3&amp;4,</td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td></td>
<td>MUAP4</td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>s2</td>
<td>MUAP1&amp;2, MUAP2&amp;3, MUAP2&amp;4, MUAP2&amp;3&amp;4,</td>
<td>MUAP2&amp;3, MUAP2&amp;4, MUAP2&amp;3&amp;4, MUAP3,</td>
<td>NONE</td>
<td>N/A</td>
</tr>
<tr>
<td></td>
<td>MUAP3, MUAP3&amp;4, MUAP4</td>
<td>MUAP3, MUAP3&amp;4, MUAP4</td>
<td></td>
<td></td>
</tr>
<tr>
<td>s3</td>
<td>MUAP2</td>
<td>MUAP2</td>
<td>NONE</td>
<td>N/A</td>
</tr>
<tr>
<td>s4</td>
<td>MUAP2, MUAP2&amp;3, MUAP2&amp;4</td>
<td>MUAP2, MUAP2&amp;3, MUAP2&amp;4</td>
<td>NONE</td>
<td>N/A</td>
</tr>
</tbody>
</table>

Table 5.14. The results from the intermediate stages of the decomposition of the superimposed waveforms.
after stage 3 (the expert system stage). Column 4 shows the certainty with which the expert system makes a decision. The results of the decomposition stage of the program show that superimposed waveform s1 was decomposed into MUAPs 1 and 2. The expert system made its decision with total certainty (1.0). The expert system decided that the other superimposed waveforms were not formed through a combination of MUAPs classified earlier with total certainty. The results from the decomposition of the superimposed waveforms were used to update the firing statistics of the MUs.

Fig.[5.42] shows the results produced by the decomposition program for the clinician after the classification of both non-overlapping and overlapping MUAPs with an updated version of the MU information. Table[5.15] gives a list of the main measurements made during the decomposition program. The decomposition program took 13 seconds to classify the 38 non-overlapping MUAPs and an additional 40 seconds to classify the superimposed waveform containing two overlapping MUAPs and to analyse the three other areas of activity classed as superimposed waveforms. The decomposition program definitely identified four MUs in the EMG signal. This result compares favourably with the observation made by the doctor that there were at least four active MUs in the EMG signal. The observation made by the doctor that there was a large variability between MUAPs is this time backed up the decomposition program (see the overprinting of MUAPs from the same MU in Fig.[5.39]). A graph of the MUAP measurements made by the doctor and the MUAP measurements made by the decomposition program is shown in Fig.[5.43]. The graph shows that the MUAPs classified into MU groups by the decomposition program are similar in size to the MUAPs measured by the doctor.
Fig.[5.42]. An update of the results of the analysis after the decomposition of superimposed waveforms.
Table[5.15]. Main measurements of results from decomposition program after the classification of non-overlapping and overlapping MUAPs.

<table>
<thead>
<tr>
<th></th>
<th>measurements</th>
</tr>
</thead>
<tbody>
<tr>
<td>MUUs found</td>
<td>4</td>
</tr>
<tr>
<td>MUAPs / MU found</td>
<td>10 10 10 10</td>
</tr>
<tr>
<td>Duration of MUAPs (ms) - Mean ± SD</td>
<td>8.8 ± 3.3 3.6 ± 0.2 3.1 ± 0.5 3.8 ± 0.4</td>
</tr>
<tr>
<td>Peak to peak amplitude of MUAPs (uv) - Mean ± SD</td>
<td>1814 ± 71 512 ± 8 403 ± 8 361 ± 4</td>
</tr>
<tr>
<td>Firing period of MUs (ms) - Mean ± SD</td>
<td>70.2 ± 6.1 66.6 ± 5.2 68.3 ± 9.0 70.0 ± 6.0</td>
</tr>
</tbody>
</table>
Fig. [5.43]. A graph showing the similarity between the MUAP measurements made by the clinician and the MUAP measurements made by the decomposition program.
6.1 Conclusions

The research work undertaken in this thesis has resulted in several new signal processing techniques being applied to the decomposition of EMG signals.

Simple digital filtering algorithms have been designed to reduce background noise in EMG signals. MUAPs in an EMG signal have been described by a set of features that have been weighted by a method known as diagonal factor analysis so that the features are uncorrelated with each other. An adaptive clustering technique has been designed to group together MUAPs from the same MU using the uncorrelated weighted features. Superimposed waveforms containing overlapping MUAPs have been decomposed accurately by using a combination of MUAP shape analysis and MU firing statistics information. An expert system has been designed to make the final decomposition decisions in order to overcome the problems associated with incomplete and uncertain information that are available.

The decomposition program achieved one hundred percent accuracy in classifying the number of MUs present in a simulated EMG signal. The decomposition program achieved an accuracy always greater than ninety five percent in classifying the MUAPs in a simulated EMG signal into their correct MU groups. Up to six MUs have been decomposed from an EMG signal. The decomposition program takes about fifteen seconds to classify all non-overlapping MUAPs in an EMG signal of length one second. On average, an extra nine seconds is required to classify every superimposed waveform in an EMG signal. The measurements of the MUAPs classified by the decomposition program in a simulated EMG signal had an accuracy of greater than eighty five percent with the MUAPs used to form a simulated EMG signal. The accuracy of the results produced by the decomposition program is the same as the accuracy of the results produced by McGill et al. (1985) in their attempt to decompose EMG signals.
The results of Case Study [R1] showed that the observation made by the experienced doctor about the number of MUs in the EMG signal was the same as the decision made by the decomposition program. The difference in measurements between the doctor and the program of the MUAPs in the EMG signal was no greater than ten percent. The decomposition program found eight more MUAPs in the EMG signal in comparison with the doctor because the program was able to decompose superimposed waveforms.

The results of Case Study [R2] showed a small difference in measurements between the doctor and the program of the MUAPs in the EMG signal. The existence of more activity in the EMG signal made it more difficult for the doctor to make a decision on the number of active MUs in the signal based on a visual analysis of the data. The doctor could only suggest that there were at least four MUs in the signal. The decomposition program was able to confidently classify three MUs in the signal and suggest a fourth possible MU. The program decomposed one superimposed waveform in the EMG signal into MUAPs from two of the three MUs classified. The program could backup its arguments with a comprehensive display of the MUAPs classified and the locations of the MUAPs in the EMG signal.

The results of Case Study [R3] again showed a small difference in measurements between the doctor and the program of the MUAPs in the EMG signal. The doctor did not classify any of the MUAPs into MU groups because of the complexity of the signal and only suggested the possibility of there being four active MUs in the EMG signal. The doctor observed a large variability between MUAPs in the EMG signal. The decomposition program confidently classified four active MUs in the signal. The decomposition program also backed up the observation made by the doctor that there was a large variability between MUAPs in the EMG signal by displaying MUAPs classified from each MU overlaid on one another. The program decomposed one superimposed waveform in the EMG signal into MUAPs from two of the four MUs classified.

Some of the benefits a doctor and patient can gain by using the decomposition program are described below:
• (a) In clinical practice a doctor has to set a triggering level manually on the EMG recording equipment to separate the background activity from the MUAP activity in the EMG signal while holding the electrode still in the muscle. This is a difficult operation and the doctor’s movement during this procedure causes an excessive amount of noise to be recorded in the EMG signal. The manual setting of a trigger level is also time consuming. The decomposition program overcomes these problems by automatically extracting the MUAP activity from the background noise with a high level of accuracy. The doctor can therefore concentrate more on holding the electrode still in the muscle and therefore reduce the noise levels in the EMG signal. The time to extract the MUAP activity is also dramatically reduced with the new method.

• (b) The doctor has no easy way of storing quantitative information about the MUs in the EMG signal. He/she has to rely on qualitative descriptions of the signal which are observed during an examination. The decomposition program solves this problem by supplying a comprehensive set of quantitative measurements on the MU information in the EMG signal for the doctor.

• (c) The doctor records an EMG signal at low percentage levels of a patient’s maximum voluntary contraction to reduce the complexity of the signal and to enable a simple visual analysis of the MUAPs present. This causes other problems because only a small number of MUs can be captured each test. Therefore, a large number of tests are required to collect sufficient MU information for a diagnosis to be made. The repeating of tests also means re-inserting the needle electrode into the muscle of the patient. This is painful for the patient and can restrict the number of tests that can be performed. Another problem is that muscle fibres activated at higher force levels only, cannot be analysed. This might lead to a false representation of the overall muscle. The decomposition program reduces these problems because it can extract MU information from an EMG signal recorded at fairly high percentage levels of a patient’s maximum voluntary contraction. More MU information can therefore be gained from an EMG signal each test and thereby reduce the number of tests required. The discomfort caused to the patient is
reduced and the time for an examination is shortened. A better representation of the MU activity in a muscle overall is also given, because MUs activated at fairly high force levels are analysed.

- (d) The doctor has great difficulty classifying superimposed waveforms formed from overlapping MUAPs and has no way of validating his/her conclusions. The decomposition program overcomes these problems and automatically decomposes superimposed waveforms into their MUAP constituents. The decomposition program aims for a fast implementation of the decomposition method while achieving an accurate result. A fast implementation of the superimposed waveform decomposition is achieved (in comparison with previous automatic methods), by splitting the method into three stages. The complexity of each stage increases as the number of MUAP combination candidates forming a superimposed waveform is reduced. The accuracy of the decomposition is achieved by the use of an expert system which deals with uncertain reasoning. The expert system gives a certainty to each result and also allows the user to question the conclusions made. The decomposition program avoids the situation of yes / no answers which reduces confidence in the results.

In conclusion, the decomposition program would be of great benefit to the doctor as an aid to diagnosing neuromuscular diseases. Time would be saved in an examination, EMG analysis results would be quantified, the discomfort to a patient reduced and the accuracy of a diagnosis increased.

6.2 Future work

6.2.1 Software developments

The decomposition program assumes that the maximum euclidean distance between adjacent MUAPs in the network that are from the same MU is smaller than the minimum euclidean distance between adjacent MUAPs in the network that are from different MUs. This is usually true, but in some circumstances the maximum euclidean distance between MUAPs from the same MU is larger than the minimum euclidean distance between MUAPs from different MUs because of the order in which
the network was formed. An incorrect MUAP classification results. This problem can be overcome in the future by some additional calculations in the MUAP classification procedure. A network can be formed N times (where there are N AcSs in the EMG signal) using a different AcS from the EMG signal as the first segment in the network each time. All the networks can then be split into clusters representing different MU groups and the results compared. The MU groups that are most common among the different network clusters are then used for the next stage of the analysis. This will avoid the situation of relying on the order in which AcSs are chosen to form a network.

6.2.2 Hardware developments

Work should be done in the future to improve the hardware side of the project. The existing program is run on an IBM compatible DELL 386SX PC machine (with maths co-processor) under the MS-DOS operating system. A personal computer was chosen for the project because of its portability within a hospital and the relative inexpense of the computing facility. The problem with using a personal computer is that the EMG analysis program is limited by the speed and memory capacity of the machine. The length of the EMG data that can be analysed by the program is restricted by the memory capacity of the machine and the MS-DOS operating system (six hundred and forty kilobytes).

The use of extended memory on the 386SX machine is not sufficient to solve the memory problems of the EMG analysis program because of the limitations of MS-DOS. A possible solution to the problem is to either use the more powerful OS/2 operating system (run on a 386 machine) which allows the user direct access to the extended memory of the machine or to use the software package Windows 3.0 combined with MS-DOS which achieves the same goals.

The speed of the analysis can be increased by using a more powerful IBM compatible 386 PC machine with a much faster clock speed. The computer could also use a digital signal processing (DSP) board (for example the Texas Instruments TMS320C25 DSP board) working in parallel with the main processor to perform tasks such as filtering and numerical analysis routines. This would dramatically increase the speed of the program.
6.2.3 Expert systems

More testing of the expert system DEMGES is required because the effectiveness of the fuzzy reasoning mechanism of the expert system will only be determined through an extensive validation study. The usefulness of the knowledge based decomposition scheme can be extended in the future by the inclusion of deep knowledge in the form of pathophysiological models. The expert system would then be able to suggest a probable disease hypothesis and to suggest other tests that should be performed to support or refute that hypothesis.

The new decomposition method is part of a large SERC project being carried out at Leicester University to provide the doctor with a large amount of EMG information to aid a clinical diagnosis. This involves the use of a large expert system. The expert system is called upon to manage several loosely coupled tasks, for example signal processing, interpretation of results, management of the consultation and presentation of results to the user. The expert system uses a blackboard system architecture rather than a rule based model because the blackboard system provides the modularity, dynamic control and efficiency needed. The blackboard system architecture contains a set of knowledge sources (one knowledge source is the new decomposition method described), a hierarchically organised blackboard and scheduling control mechanisms. Fig.[6.1] shows a block diagram of the architecture of the blackboard system (taken from Sehmi et al., 1991 - appendix 6).

During a clinical examination the expert system will incrementally construct a picture of the current status of the patient from available measurements, analysis methods performed and clinical observations until a clinical diagnosis can be made.

6.2.4 Neural networks

Another way to expand the usefulness of the new decomposition method is the inclusion of a neural network. A neural network is a processor of information consisting of simple processing elements connected together. Each processing element is a very simple model of a neuron in the brain (Bishop and Mitchell, 1991). Each element stores experimental knowledge after a process of learning from task examples (Aleksander and Morton, 1990).
Fig. 6.1. The blackboard distributed knowledge-based software architecture (taken from Sehmi et al., 1991).
MUAP information produced by the existing decomposition method could be fed into a neural network with other clinical measurements. The neural network would then decide if the input information indicated the existence of a disease. Fig.[6.2] shows a schematic diagram, describing the use of a neural network. The result would give an indication of the level of disease rather than a yes/no answer to whether a disease exists or not.

Fig.[6.2]. A schematic diagram of the use of a neural network.

The neural network would perform a pattern recognition analysis on the MUAP waveforms classified in the decomposition method. The neural network would contain a set of MUAP templates representing different types of normal and diseased MUAP waveforms. The classified MUAPs would then be matched with the different MUAP templates and the MUAP templates most similar to the classified MUAPs recorded. The degree of similarity between the classified MUAPs and the MUAP templates
would also be noted. The MUAP templates selected as the most similar MUAP waveforms would give information on the type of disease present. The *degree of similarity* between the MUAP templates selected and the MUAPs classified would give an indication of the severity of the disease.

Neural networks are powerful tools in the field of decision making because they have the potential for performance improvement as they acquire more knowledge about the domain over time; they are able to handle fuzzy data, that is they are able to learn and then recognize certain data patterns and those which are similar; they are also inherently parallel in their operation and therefore have the ability to operate much faster than conventional computer programs (Bishop and Mitchell, 1991).

The use of a neural network for the suggestion of a disease hypothesis would eliminate the requirement for a large expert system as described above because of the advantages of neural networks over expert systems.
References


Appendices
Appendix 1

A Selective Non-invasive Electrode to study Myoelectric Signals

(published in the Medical & Biological Engineering & Computing journal, November 1990)
Transducers and electrodes

Selective noninvasive electrode to study myoelectric signals

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Abstract—The paper describes the design and construction of a selective surface electrode for use in a clinical environment. The main criterion of the design was to enable the recognition of individual motor unit action potential trains (MUAPs) at moderate force levels. The main features of the electrode are, first, a small concentric bipolar arrangement to avoid electrode/muscle fibre alignment problems and to allow measurements within a small, well defined probed volume; secondly, the nonrequirement for conducting paste or gel; and thirdly, the casing acting as an earth plate. All of these simplify its use. The results of tests undertaken with the electrode showed that it was able to pick up individual MUAPs at up to 20 per cent of maximum voluntary contraction from the first dorsal interrosseous muscle. Tests were carried out on the small hand muscles to further demonstrate the usefulness of the electrode. A computer program was written to calculate the shift in frequency of the power spectrum of the recorded myoelectric signal with muscle fatigue and hence indirectly to demonstrate the ability of the electrode to detect the reduction in muscle fibre conduction velocity.

Keywords—Electrodes, Myoelectric signals, Selectivity, Motor unit, Action potential train, Muscle fibre conduction velocity

Introduction

Muscle fibres are activated by impulses sent down motor nerves from the spinal cord. Each nerve impulse innervates a group of muscle fibres known as a motor unit (MU). As the impulse is received by the muscle fibres, the permeability of muscle fibre membrane is changed and it becomes temporarily depolarised. This depolarisation passes to adjacent regions of the membrane so that a wave of electrical potential, the so-called action potential, propagates along each muscle fibre. This may be detected using various types of electrodes and the observed waveform is known as the motor unit action potential (MUAP). The shape of the MUAP waveform depends not only on that of the depolarisation waveform but also on the characteristics of the electrode and its position and orientation relative to the muscle fibres. During a muscular contraction, trains of impulses are sent down the motor nerves. The waveform observed using an electrode is a superposition of different MUAP trains and is known as the myoelectric or EMG signal (Basmajian and Delluca, 1985).

The shapes of the MUAP waveforms in a myoelectric signal are an important source of information used in the diagnosis of neuromuscular disorders (Ludin, 1980). However, as the force level of a muscular contraction increases, the frequency of the MUAP trains also rises and it becomes increasingly difficult to identify the individual shapes of the overlapping MUAP trains. Although this problem may be lessened by using invasive electrodes which monitor only very localised regions of muscle, such needle or wire electrodes suffer from various disadvantages. These include causing discomfort to the patient, difficulty of use in uncooperative patients such as children and causing damage to the muscle. The number and duration of measurements possible with them are therefore limited.

The noninvasive (or surface) electrode developed in this work was designed to probe a much smaller area than conventional noninvasive electrodes. It would thereby reduce the number of overlapping MUAP trains recorded at a given level of muscular contraction and make it simpler to identify individual MUAP waveform shapes. Although it was not expected to be as selective as invasive electrodes, it was designed to be more selective than conventional noninvasive electrodes and considerably simpler to use than both.

Noninvasive electrodes may be either active or passive. In the passive configuration, the leads connecting the electrode to the detection instrument may present a considerable capacitance. Low-impedance skin/electrode interfaces using conductive pastes or gels are required so that current can flow to charge this capacitance as the skin potential changes. Active (or pasteless) electrodes have an integral, high input impedance, low output impedance amplifier so that there is virtually no capacitance seen by the electrode,
and it is consequently insensitive to the impedance of the skin/electrode interface. Because of their ease of use, active electrodes are becoming more common in the clinical environment and it is such an electrode that is described here.

2 Electrode requirements

Discussions involving clinicians experienced in the field of electromyography yielded some important requirements of an electrode. These requirements, which were satisfied by the electrode developed, are summarised below.

2.1 Physical requirements

Some of the physical requirements reflect the fact that the electrode was designed especially for studying small muscles. The physical requirements are:

(a) It should cause as little discomfort to the subject as possible; a needle electrode should be avoided if possible.
(b) It should avoid the problem of aligning the electrode to the direction of the muscle fibres.
(c) It should not require a conductive paste or gel between the skin and the electrode surface.
(d) It should be easy to use and small in size.

2.2 Electrical requirements

The electrical requirements of the active electrode are determined to a large extent by the amplitude of the MUAP, the skin/electrode interface resistance and the required bandwidth. Typically, a MUAP is about 0.5 mV for a bipolar needle electrode (Jones, 1981). Several measurements were made of the dry skin/electrode interface resistance and it was found that the resistance rarely exceeded $10^0 \Omega$. The electrical requirements are:

(a) It should be a bipolar (differential) electrode, in order to overcome the problem of common mode noise. DeLuca et al. (1979) recommended that the common mode rejection ratio (CMRR) of the differential amplifier should be at least 5000 (74 dB) at 50–60 Hz to prevent mains interference.
(b) As the skin/electrode interface resistance does not exceed $10^1 \Omega$, the differential input resistance of the electrode should be $>10^3 \Omega$ to prevent attenuation of greater than 1 per cent. The skin/electrode interface forms a low-pass filter with the electrode capacitance. For good response to 1 kHz this capacitance must be $<1/(2\pi \times 10^3 \times 3 \times 10^0 \Omega) = 16 \mu F$. In practice this small capacitance is probably the most difficult requirement to meet.
(c) The DC input bias current produces a polarisation potential which appears across the skin/electrode interface resistance and should therefore be kept as small as possible (DeLuca et al., 1979). The polarisation potential is unlikely to cause electrochemical effects below 100 mV (corresponding to energies of $\sim 10 kJ mol^{-1}$), and while 100 mV is a large common-mode signal, compared with a MUAP of $\sim 0.5 \text{mV}$, it is DC and can be eliminated with a low-frequency high-pass filter. The DC input bias current should therefore be $<10 \text{nA}$ ($=100 \text{mV}/10^0 \Omega$).
(d) The AC output impedance should be low to reduce any signal attenuation or common-mode imbalance caused by the capacitance of the output cable and to reduce the effects of 50 Hz inductive pick-up and motion artefacts. DeLuca et al. (1979) suggest this should be $<2 \text{k} \Omega$, which is well within the capabilities of most modern instrumentation amplifiers.
(e) The active circuitry should provide a relatively high gain for the myoelectric signals. As they are not likely to exceed a few millivolts, gains of up to $1000 \times 10^0 \text{dB}$ could be envisaged provided the response at high frequencies was not compromised by the bandwidth or slew rates of the amplifier.
(f) The whole electrode casing should be earthed for safety and for screening against electrostatic pick-up. This may also be used to obviate the requirement of a separate earth strap.
(g) The electrode should respond to frequencies in the range 15 Hz–1 kHz. Previous researchers (Agarwal and Gottlieb, 1975; Kwatny et al., 1970) have recorded myoelectric signals with a bandwidth of 15 Hz–500 Hz using surface electrodes. However, it can be argued that significant power should exist in the signal above 500 Hz (as recorded from needle electrodes) and the reason it has not been recorded is because of the surface electrode design. To facilitate the study of selective surface electrodes a bandwidth of 15 Hz–1 kHz is chosen.

3 Design and construction

It was found that the above requirements could be achieved by a dry concentric bipolar electrode with an instrumentation amplifier mounted very close to the recording surfaces. After studying different electrode configurations the following design resulted.

The electrode recording surfaces are two concentric steel rings. A third ring attached to the casing of the electrode is the earth contact. The rings are separated from each other by the insulating material PTFE (Teflon). Fig. 1 shows a schematic diagram of the electrode configuration.

![Schematic diagram of the electrode configuration](image)

The small surface area of the electrode plates, the small physical size and the concentric arrangement produce the effect of recording signals mainly from fibres near to the axis of the electrode and thereby make the electrode much more selective. The concentric ring instead of the normal passive electrode configuration also obviates the problem of electrode alignment relative to the direction of the muscle fibres.

An analysis of the filtering characteristics of the electrode is described below. The mathematical derivations show how the concentric arrangement and small inter-detection spacing contribute to the electrode's performance. The analysis follows the methods developed by Lindstrom (1970) for conventional bipolar passive surface electrodes.

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Fig. 2 defines the geometry used by Lindstrom in his modelling of the myoelectric field for a single muscle fibre signal. The diagram shows the new concentric ring electrode configuration (no earth ring is shown). The length of the muscle fibre is assumed to be large in comparison with the distance between the electrode and muscle. It is also assumed that the tissue medium is electrically isotropic and linear. The propagation velocity of the muscle fibre wavefront is between 2 and 6 m s⁻¹ (LINDSTROM, 1970).

Lindstrom showed that, for a conventional bipolar passive electrode, with two parallel electrode contacts at \( x_o - d \) (noninverting electrode) and \( x_o + d \) (inverting electrode), the Fourier component \( \Delta \psi \) of the potential difference from the total fibre was:

\[
\Delta \psi(\omega) = \psi(\omega)_{x_o - d} - \psi(\omega)_{x_o + d}
\]

(1)

where \( \psi(\omega)_{x_o - d} \) and \( \psi(\omega)_{x_o + d} \) are the potentials at the noninverting and inverting electrode positions, respectively. Lindstrom then represented the potentials in terms of the geometry of the electrode in relation to the muscle fibre, the propagation velocity \( v \) and frequency components \( \omega \) of the muscle fibre wavefront. He showed that at position \( x \):

\[
\Delta \psi(\omega) = 2 \exp(-j \omega x_o / v) \times \left( K_{\alpha}(\omega h/v) / K_{\alpha}(\omega a/v) \right) \times \int_{-\infty}^{\infty} \phi(t) \exp(-j \omega t) dt
\]

(2)

where \( \phi(t) \) is the potential at the muscle fibre surface and \( K_{\alpha} \) is the modified Bessel function of the second kind and order zero. Hence,:

\[
\Delta \psi(\omega) = 2 \exp(-j \omega x_o / v) \times \left( \exp(j \omega d / v) - \exp(-j \omega d / v) \right) \times \left( K_{\alpha}(\omega h/v) / K_{\alpha}(\omega a/v) \right) \times \int_{-\infty}^{\infty} \phi(t) \exp(-j \omega t) dt
\]

(3)

\[
= 4 \exp(-j \omega x_o / v) \sin(\omega d / v) \times \left( K_{\alpha}(\omega h/v) / K_{\alpha}(\omega a/v) \right) \times \int_{-\infty}^{\infty} \phi(t) \exp(-j \omega t) dt
\]

(4)

Lindstrom used the terms in eqn. 4 to find the effect they had on the power spectrum of the myoelectric signal. He identified different filtering terms in the equation that caused attenuation of myoelectric signals. The sine term described the filtering function caused by the electrode configuration and caused certain frequencies of the myoelectric power spectrum to be filtered out.

The Fourier component \( \Delta \psi \) of the potential difference from the total fibre can be calculated using Fig. 2 for the new concentric ring surface electrode to find the effect of its configuration. The calculations assume that the outer (inverting) ring sees the average of the signals at \( x_o - d \) and \( x_o + d \). The Fourier component \( \Delta \psi \) of the potential difference from the total fibre is:

\[
\Delta \psi(\omega) = \psi(\omega)_{x_o - d} - 1/2(\psi(\omega)_{x_o - d} + \psi(\omega)_{x_o + d})
\]

(5)

where \( \psi(\omega)_{x_o - d} \) and \( 1/2(\psi(\omega)_{x_o - d} + \psi(\omega)_{x_o + d}) \) are the potentials at the noninverting and inverting electrode surfaces, respectively.

Following Lindstrom’s analysis:

\[
\Delta \psi(\omega) = 2 \exp(-j \omega x_o / v) \times \left( 1 - 1/2(\exp(j \omega d / v) + \exp(-j \omega d / v)) \right) \times \left( K_{\alpha}(\omega h/v) / K_{\alpha}(\omega a/v) \right) \times \int_{-\infty}^{\infty} \phi(t) \exp(-j \omega t) dt
\]

(6)

\[
= 4 \exp(-j \omega x_o / v) \sin^2(\omega d / 2v) \times \left( K_{\alpha}(\omega h/v) / K_{\alpha}(\omega a/v) \right) \times \int_{-\infty}^{\infty} \phi(t) \exp(-j \omega t) dt
\]

(7)

The effect of the electrode configuration has caused the sine term in eqn. 7 to be squared and its angle to be half that of the passive bipolar electrode. The concentric ring has the effect of doubling the propagation velocity term \( v \) of the muscle fibre wavefront and therefore producing sharper recorded spikes. Fig. 3 shows a plot of calculated filter functions against frequency (the relative amplitude scales of the electrodes are arbitrary). The differing filter function characteristics are caused by the new electrode configuration and the interdetection spacing.

The dips in the filtering function of the new electrode occur at higher frequencies than for the passive electrode, therefore filtering out less myoelectric signal information. The derived filtering function suggests that the new electrode would be better at filtering out low-frequency noise. However, at low frequencies the wavelength becomes comparable to the dimension of the tissue medium and the assumptions made in the analysis begins to fail. It will be seen that the responses of the two electrodes are, in fact, similar at low frequencies.

Fig. 3 Plot of surface electrode filter function against frequency

- - - - passive electrode where \( 2d = 20 \) mm and conduction velocity \( = 5 \) m s⁻¹
- - - - new electrode where \( 2d = 13 \) mm and conduction velocity \( = 5 \) m s⁻¹

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Fig. 4 shows the prototype electrode that was constructed. An instrumentation amplifier (INA101) was mounted directly on the back of the electrode. Details of the measured electrical impedance characteristics are given below and fit well with the electrical requirements stated previously.

Common-mode rejection ratio = 85 dB (unity gain)
Input capacitance = 4 pF (i.e. 3 per cent attenuation at 1 kHz)
Input resistance = \(10^{12}\) Ω
Input bias current = 15 nA
Gain = 40 (32 dB).

The voltage gain chosen for the electrode was \(40\) (32 dB), as this gave signal amplitudes comparable with a conventional passive electrode and was convenient for purposes of comparison.

4 Tests and results
Tests were carried out on arm and hand muscles using both the passive and new electrodes (see Fig. 4). The passive electrode used was a conventional bipolar electrode with 20 mm interdetection spacing (Medelec SE20 sensory recording electrode). An example of traces recorded with the two electrodes from the first dorsal interosseous muscle at 20 per cent maximum voluntary contraction is shown in Fig. 5. It can be seen that MUAP trains are clearly identifiable in the myoelectric signal recorded with the new electrode. Even at higher force levels, a doctor would be able to gain valuable information from the MUAP shapes that exist in the signal and form assessments of the likelihood of disease. The conventional bipolar passive electrode is less selective and therefore records more MUAP trains than the new electrode at the same force level. The superposition of the MUAP trains in the conventional electrode results in a loss of individual MUAP shape information.

Power spectra were recorded from different muscles in the arm and hand. Typical power spectra recorded from the first dorsal interosseous muscle using the passive and new electrode are shown in Fig. 6. The power spectra contain features that relate to the theoretical filter functions of the different electrode configurations. The spectrum of the signal from the passive electrode exhibits a sharp cutoff at 150–200 Hz (\(f_1\) on Fig. 3) which is not observed with the new electrode. This is in agreement with the filter function calculations (Fig. 3). Above this frequency myoelectric activity is again observed with the passive electrode but this is reduced and sharply attenuated at 300–400 Hz (\(f_2\) on Fig. 3), again in agreement with Lindstrom's calculations. The spectrum of the signal from the new electrode appears to cut off at about 400–500 Hz in agreement with our calculations. The concentric ring electrode has attenuated the high-frequency components of the myoelectric signal less than the conventional bipolar passive electrode. Below about 100 Hz the power spectra of the signals from both electrodes do not cut off as fast as might be expected from the theoretical calculations. This might be the result of high levels of noise caused by electrode movement but may also be because some of the theoretical assumptions become invalid at low frequencies.

Simple clinical tests to demonstrate the usefulness of the electrode have been performed on hand muscles to study the reduction in muscle fibre conduction velocity that occurred when a subject maintained a constant force for a set period of time (i.e. a fatigue test). This has been achieved by studying the change in the power spectrum of the myoelectric signal. The new electrode allowed quick
and easy tests to be performed. A brief summary of these tests is given below.

4.1 Apparatus
The apparatus used in the clinical tests involved a force machine (MAGLOAD) (Jones et al., 1987) to produce a constant force level (at which a subject maintained an isometric contraction), an amplifier and filtering equipment (Medelec Modular Electrophysiological System), an A/D convertor (CED1401) and a microcomputer (Olivetti M24).

4.2 Method
A computer program was written in C to calculate the power spectrum of the myoelectric signal before and after the muscle had been fatigued. The first set of data (4 s pre-fatigue) was collected as soon as the subject was in the correct position and maintaining a 50% per cent maximum voluntary contraction. This force level was maintained continuously for another 30 s when a second set of data (4 s post-fatigue) was collected.

The median frequency of the power spectrum was used to calculate the percentage change in muscle fibre conduction velocity. This was based on the work done by Stulen and DeLuca (1981) which showed that there is a linear relationship between the reduction in muscle fibre conduction velocity and the reduction in median frequency of the power spectrum that occurred with fatigue. Many previous researchers have proved that the main causes of median frequency reduction in the power spectrum with fatigue is the change in muscle fibre conduction velocity (Basmajian and DeLuca, 1985).

4.3 Results
Results recorded from the first dorsal interosseous muscle of 15 subjects showed a reduction in the median frequency of the power spectrum, indicating a slowing down of the muscle fibre conduction velocity after fatigue.

![Histogram of muscle fibre conduction velocity reduction after fatigue](image)

Fig. 7 Histogram of muscle fibre conduction velocity reduction after fatigue

Fig. 7 shows the distribution of the percentage reductions in muscle fibre conduction velocity that were obtained in all 15 subjects. The differences in reductions obtained could be accounted for by:

(i) the state of the muscle before the test, which varied from person to person, as some would be fresher than others
(ii) the general physical health of the individual
(iii) the test conditions being reliable and repeatable for different subjects.

The results indicate that the new electrode, in normal use, is detecting a known physiological change, which normally requires directional electrodes or very careful placement of conventional electrodes.

5 Applications
The information obtained on muscle fibre conduction velocity can aid the clinician in following the development of disorders such as neuropathies induced by lesions of the peripheral motor neurones (Basmajian and DeLuca, 1985).

The new electrode developed has been used in conjunction with research work undertaken in the decomposition of myoelectric signals (Loudon et al., 1989) which, up to now, has required needle electrodes to provide the selectivity needed to detect individual motor unit action potential trains.

The new electrode’s selectivity and ease of use allows the clinician to perform quick myoelectric recordings while reducing the discomfort to the patient caused by needle electrodes.

Acknowledgments—We wish to thank Dr V. Brazinova (Leicester Royal Infirmary) for her help in evaluating the electrode. We acknowledge the SERC for a studentship for Mr G. Loudon. We also acknowledge Medelec Ltd for their sponsorship of Mr G. Loudon.

References


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N. B. Jones was born in Liverpool in 1941. He obtained his B.Sc. in Electrical Engineering from Manchester University in 1962, was a graduate apprentice with BICC, obtained the M.Eng. from McMaster University, followed by more industrial experience in Canada. He obtained the D.Phil. degree in Control Engineering from the University of Sussex in 1968, and worked on various aspects of bioengineering there until 1984, specialising in control and signal processing applied to neurology and vascular surgery. He is now Professor of Engineering at the University of Leicester, where he is continuing the research lines already mentioned.
Appendix 2

Intelligent classification in EMG decomposition

INTELLIGENT CLASSIFICATION IN EMG DECOMPOSITION
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Abstract
This paper presents research relating to the use of computers for the intelligent decomposition of myoelectric signals (EMG). A knowledge based expert system is described which decomposes superimposed waveforms formed from overlapping motor unit action potentials (MUAPs) in a myoelectric signal using symbolic information provided by numerical recognition analysis. The system, written in Prolog, consists of some 30 rules in the knowledge base that are driven by an interpreter that incorporates uncertain reasoning based on fuzzy set theory. The expert system contains both procedural and declarative knowledge representations of the problem domain. The declarative rules contain a description of the relationships between the raw motor unit (MU) information collected by the numerical analysis and the superimposed waveforms being decomposed. The procedural rules interact with the declarative rules through rule attachments that activate demon procedures. The demon procedure computes fuzzy certainty factors for all the possible combinations of MUAPs that form a superimposed waveform.

Keywords: Knowledge based Signal Processing, Electromyography, Decomposition.

1 Introduction
The manual assessment of myoelectric data by human experts is based upon complex processes of data reduction and feature extraction, some of which are apparently subjective. The complete task of data evaluation and interpretation falls largely on the human expert who uses an holistic view of the data collected, in conjunction with some simple quantitative measures which can be calculated by computer based algorithms. Since our aim is to fully decompose and interpret myoelectric signals automatically in a computer, the holistic reasoning that a human expert uses must be simulated. The simulation of this reasoning is performed using knowledge based expert system techniques.

2 The Application Domain
The electrical activity recorded from a muscle when under contraction is known as the myoelectric or emg signal. The myoelectric signal results from the activation of groups of muscle fibres by impulses sent down motor nerves from the spinal cord. Each nerve impulse innervates a group of muscle fibres known as a motor unit (MU). The resultant waveform recorded from a MU is known as the motor unit action potential (MUAP) (Basmajian and DeLuca,1985). During a constant force contraction, trains of impulses are sent down the motor nerves at fairly regular intervals resulting in a train of MUAPs. The firing period distribution of nerve impulses is almost gaussian with a very small variance (Andreassen and Rosenfalck,1980). The resultant myoelectric signal recorded with needle or surface electrodes is then a summation of the individual MUAP trains from different MUs in the muscle. The signal is called the interference pattern EMG (IPEMG).

The shapes of the MUAP waveforms in a myoelectric signal are an important source of information used in the diagnosis of neuromuscular disorders. The objective of our research is to intelligently decompose the IPEMG into its individual MUAP trains under fairly high force level conditions (say 30% maximum voluntary contraction). This requires the classification of both non-overlapping MUAPs and the decomposed superimposed waveforms formed from overlapping MUAPs in the signal. Non-overlapping MUAPs are classified using a statistical pattern recognition method. The method first describes the MUAPs by a set of features and then uses diagonal factor analysis to form uncorrelated factors from these features (Gorsuch,1974). An adaptive clustering technique groups together MUAPs from the same MU using the uncorrelated factors (Tryon,1970).

The decomposition of superimposed waveforms is divided into two sections. The first section is a procedural method that finds a reduced set of all possible combinations of MUAPs which are capable of forming each superimposed waveform by using a template matching procedure. A more detailed
A description of this procedural analysis outlined can be found in Loudon et al. (1989). The second section is the knowledge-based analysis of the candidate MUAP combinations forming each superimposed waveform. This latter analysis decides which combination is the most probable (see Fig[1]).

3 Intelligent Classification of Superimposed Waveforms

It is possible for a machine to decompose a superimposed waveform into its constituent MUAPs. However, with current methods of decomposition either errors will result, the time taken for decomposition is very long (LeFever and DeLuca, 1982) or much training is required to use the decomposition scheme. Errors could be due to noise in the signal or because of the similarity between results after a pattern matching analysis. Human experts are able to identify which of the possible MUAP combinations comprise a superimposed waveform by studying the firing times of the MUAP trains (Basmajian and DeLuca, 1985). Typically they would arrive at a decision based on uncertain and incomplete evidence available from the MU firings already classified. This observation has led to the specification of an expert system which uses a fuzzy reasoning model to describe the decomposition protocol of superimposed waveforms.

Candidate MUAPs as provided by procedural decomposition method

Figure 1: Functional diagram of the DEMGES expert system.

Fig. [1] Functional diagram of the DEMGES expert system.
3.1 Fuzzy Certainty Factor Calculations in DEMGES

DEMGES is an acronym for Decomposition of EMG Expert System. It is a suite of programs used to automatically decompose myoelectric signals and it includes the preliminary numerical analysis programs. DEMGES uses fuzzy certainty factors to model its uncertain reasoning mechanism so that intelligent classification of superimposed waveforms can be performed. The fuzzy membership functions are described by the firing period statistics of the partially classified MUs.

The rules that DEMGES contains are modelled on the judgemental processes that an expert uses for superimposed waveform decomposition. The information provided by the numerical analysis is examined by DEMGES rules in the early stages of a goal-directed reasoning process. MUAP candidates in a combination selected from the numerical analysis are given fuzzy values which are propagated through the search space towards the final goal of finding the certainty of a MUAP combination forming a superimposed waveform. Hence, the numerical analysis results are easily assigned qualitative descriptions for the expert system to reason with.

The method by which fuzzy values are assigned to the MUAP combinations relies on the definition of a fuzzy model describing the myoelectric signal. The model is described next, and is comprised of two parts, namely the procedural and the declarative model components.

3.2 The Fuzzy Procedural Model (Database)

The fundamental primitive for information modelling is propositional statements of the form : an attribute of an object has a particular value. This is represented in the Prolog language as the symbolic structure -

Object Attribute Value

Again in Prolog, we may express that a MUAP candidate in a combination definitely occurs at exactly the position of a superimposed waveform X by writing :-

MUAP position is X

This will not be the case in reality, because the firing times of a MU are not exactly regular. The MUAP candidates are given fuzzy values related to the possibility of a MUAP occurring at the position of a superimposed waveform. The fuzzy value is calculated using the fuzzy membership function shown in Fig[2].

![Diagram](#)

**Fig.[2]** The fuzzy membership function.
This function can be described in terms of a fuzzy set (Zadeh, 1965). Very briefly, fuzzy set theory states that a fuzzy set is a class which admits the possibility of partial membership in it. A fuzzy value of 1.0 represents full membership and a fuzzy value of 0.0 represents non-membership. Intermediate fuzzy values represent partial membership.

The fuzzy value of a MUAP candidate is calculated by mapping the smallest firing period (SFP) between the nearest neighbouring MUAP in the MUAP train and the position of the superimposed waveform onto the fuzzy membership function which describes the MU firing period distribution. In Fig[2] for example, a MUAP candidate 'A' maps to a fuzzy value of 0.9 indicating partial membership of the fuzzy set of all possible firing periods. The duration of the fuzzy function varies for each MUAP train (and hence each MU) in the myoelectric signal, depending on the mean and standard deviation of the firing period of the MU duration.

3.3 The Fuzzy Declarative Model (Knowledge base)

This model attempts to capture the expert decision making process used to decompose superimposed waveforms. The fuzzy procedural model above makes it possible to formulate propositions of the form:

\[ \text{Object Attribute Value cf Fuzz} \]

where the certainty with which a proposition holds is expressed with a propositional attachment called the certainty factor (cf) or fuzzy value. The fuzzy value Fuzz relates to the possibility of the proposition being true. Furthermore we can formulate the consequence of fuzzy propositions in Prolog by using fuzzy rules of the form:

Rule ::
if Object Attribute Value cf Fuzz
then ObjectX AttributeX ValueX cf CF.

The confidence in the rule being true can be expressed through the rule attachments CF. So the value ValueX of the object ObjectX is concluded with the combined fuzzy value computed from the fuzzy value Fuzz of the object Object and the rule confidence attachment CF. Fuzz and CF are combined by simply multiplying their values together.

The premise of a rule can contain both conjunctions and disjunctions of propositional clauses. The combined fuzzy value of a conjunction or disjunction of clauses is determined using fuzzy set theory. In a conjunction the minimum fuzzy value is taken from the computed fuzzy values in the set of clauses in the premise. In a disjunction the maximum fuzzy value is taken. For example, in the rule below, the fuzzy value of the conclusion will be computed by taking the minimum of Fuzz1 and Fuzz2 and then multiplying this by 0.95.

\[ \text{rule19 ::}
\]
if
Mean < (SFP / 1.5) cf Fuzz1 and
Firing_period is (SFP / 2.0) cf Fuzz2
then
muap( MuapNo, Mean, SD, FiringPeriod )
is_compared_with SFP cf 0.95.

Some rules in the knowledge base (e.g. rule19 above) cater for problems that arise when the SFP is much greater than the mean firing period of a MU (due to unclassified MUAPs) as shown in Fig[3]. This is done by repeating the fuzzy membership function at multiples of the mean firing period. These rules are given certainty factors that reduce in value as the SFP increases with respect to the mean firing period of a MU.
Fig. [3] Firing times of a motor unit (MU) before full decomposition of superimposed waveforms.

Fig. [4] shows the effect on confidence in the rules at increasing multiples of the mean firing period of a MU.

Fig. [4] The reduction in rule confidence as the SFP increases from the mean.

Rules are provided to calculate the overall fuzzy value of each candidate MUAP combination (Z) in a superimposed waveform. The formula used to find the overall fuzzy value is:

\[ F(Z) = F(X) \times \text{NOT}(F(Y)) \]

where \( F(Z) \) is the overall fuzzy value of a MUAP combination, \( F(X) \) is the combined fuzzy value of the intersecting set of individual MUAPs in a combination and \( F(Y) \) is the combined fuzzy value of the exclusive set of individual MUAPs not in a combination.

3.4 The DEMGES Interpreter

This interpreter shell is backward chaining and provides uncertain inference and explanation capabilities on the declarative model described in the previous section. It also provides the interfacing with the procedural model through invocation of user-defined demon-procedures. The interpreter manipulates and executes Prolog expressions making up the declarative model (ie. knowledge base) and hence, it is possible to pass goals such as the demon procedures to Prolog for execution. This facility is necessary for the evaluation of mathematical constructs and for interfacing to the "C" language which performs the initial numerical analysis. An important specification for this implementation has been
separation of all DEMGES modules. In this respect the same interpreter can be used to execute knowledge bases that will be defined in the future for further interpretation of the results produced by DEMGES for diagnostic purposes. The structure of the interpreter shell is derived from the work by Sehmi (1988) and Sehmi and Jones (1989).

```prolog
% Top call
solve(Goal) :-
solve(Goal cf Fuzz, Fuzz, []).

% Is goal known
solve(Goal cf Fuzz, Fuzz, _) :-
fact :: Goal cf Fuzz.

% Is goal solvable using a procedural call
solve(Goal cf Fuzz, Fuzz, _) :-
demon(Goal,Demon_procedure),
call(Demon_procedure).

% Is goal solvable using a rule
solve(Goal cf Fuzz, Fuzz, Stack) :-
Rule :: if Premise then Goal,
satisfy(Premise, Fuzz, (Goal+Rule|Stack)),
conclude(Goal,Fuzz,Rule).

% Ask user for solution
solve(Goal cf Fuzz, Fuzz, _) :-
askable(Goal),
assert_solution(Goal).
```

Satisfy/3 attempts to solve the clauses in Premise by recursively invoking solve/3 with each clause in turn. A successful goal will cause satisfy/3 to calculate its certainty (or fuzzy) value and eventually a combined certainty value for all the clauses in Premise. Conclude/3 will then assert the Goal into the database with the combined certainty value of Premise.

### 3.5 The User Interface

The user interface provides the facility to query the results of the myoelectric signal decomposition. Fig[5] shows a simulated myoelectric signal containing four motor unit trains. The suggestion that a superimposed waveform contains MUAPs two and three has been queried by selecting the waveform in the myoelectric signal using a mouse pointing device. A pop-up window shows the fuzzy certainty values of the result and all the other possible combinations of MUAPs that could have formed the selected superimposed waveform.

The user is given the option to study how the conclusions were formed. The how explanation displays the trace of reasoning taken by the expert system by interpreting the proof-tree built up in reaching that conclusion. The user is also able to study any rule invocations to seek a more specific explanation to a query.

### 4 Discussion

Tests are being carried out on both real and simulated myoelectric data. The effectiveness of the fuzzy reasoning mechanism of the expert system will only be determined through an extensive validation study. Deep knowledge in the form of pathophysiological models would have to be included to extend the usefulness of this knowledge based decomposition scheme in the actual diagnosis of neuromuscular disorders. The expert system would then be able to suggest a probable disease hypothesis and to suggest other tests that should be performed to confirm or deny that hypothesis.
Fig. [5] The explanation user interface with DEMGES.

5 References


Appendix 3

Intelligent decomposition and interpretation of myoelectric signals

(presented at the 6th International Conference on Biomedical Engineering, Singapore 1990)
INTELLIGENT DECOMPOSITION AND INTERPRETATION OF MYOELECTRIC SIGNALS

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SUMMARY

This paper presents research relating to the use of computers for the intelligent decomposition and interpretation of myoelectric signals. Firstly, digital filtering algorithms are used to reduce the noise in the signal. The filtered signal is then normalised and compressed to reduce the time of the analysis. The non-overlapping motor unit action potentials (MUAPs) in the myoelectric signal are identified using a statistical pattern recognition method.

An expert system has been designed to decompose superimposed waveforms formed by a summation of overlapping MUAPs. Initially, a procedural method is used to find a reduced set of all possible combinations of MUAPs which are capable of forming each superimposed waveform. The motor unit firing times are then analysed by the expert system to decide which combination of MUAPs is most probable. Production rules are used in the decision making of the expert system and are driven by an interpreter that incorporates uncertain reasoning based on fuzzy set theory.

Keywords - Electromyography, decomposition, signal processing, expert system, diagnosis.

INTRODUCTION

The myoelectric or EMG signal is the electrical activity recorded from a muscle when under contraction. The EMG signal results from the activation of groups of muscle fibres by impulses sent down motor nerves from the spinal cord. Each group of muscle fibres is known as a motor unit (MU). The resultant waveform recorded from a MU is known as the motor unit action potential (MUAP). During a muscular contraction, trains of impulses are sent down the motor nerves resulting in a train of MUAPs. For a constant force contraction, the firing period distribution of nerve impulses is almost gaussian with a very small variance. The resultant EMG signal is a summation of the individual MUAP trains from different MUs in the muscle.

Important information is gained from the shapes of the MUAP waveforms in an EMG signal and is used in the diagnosis of neuromuscular disorders. The objective of our research is to intelligently decompose the EMG into its individual MUAP trains under fairly high force level conditions (say 30% maximum voluntary contraction). This requires the classification of both non-overlapping MUAPs and the decomposed superimposed waveforms formed from overlapping MUAPs in the signal.

CLASSIFICATION OF NON-OVERLAPPING MUAPS

The classification of non-overlapping MUAPs is divided into three main sections: -
MUAP data collection, MUAP description and cluster analysis.

MUAP data collection - The EMG signal contains noise due to needle movement, background activity from distant motor units and some instrumentation artifacts. To discriminate useful signal (related to MUAPs near the electrode) from noise, the EMG signal must be processed. Firstly, a simple high pass filtering algorithm is used to eliminate any baseline drift and avoid the problem arising from electrode movement. The resultant EMG signal is then low pass filtered using a frequency-domain design FIR filter which filters out high frequency noise. Next, the EMG signal is normalised to allow for varying amplitudes of the signal and finally, the EMG signal is segmented into areas of activity where local MUAPs have been found, and areas of non-activity which contain only background noise. To reduce data storage, only the active segments (AcSs) are stored.

MUAP description - The MUAP waveforms are classified using eight shape descriptors derived from each AcS. The use of shape descriptors dramatically reduces computational time. Examples of these descriptors are: - duration, maximum peak to peak amplitude, etc.
number of turning points. One problem is that the shape descriptors of each AcS are correlated and may therefore provide limited information to discriminate between MU groups in certain data sets. In these circumstances, some shape descriptors should not be used to make a classification decision. Diagonal factor analysis (Gorsuch, 1974) is performed to find weightings (importance) for each shape descriptor. Diagonal factor analysis weights the descriptors such that they become uncorrelated and hence better at discrimination. The non 'zero-weighted' shape descriptors describing each AcS are used to form n orthogonal n-dimensional vectors in vector space.

Cluster analysis - Cluster analysis groups together AcSs of similar shape. The euclidean distances between the vectors of the AcSs are used to study how similar the shapes of the AcSs are. Each AcS’s nearest neighbour (relating to shape similarity) is found and a network is formed (Tryon and Bailey, 1970). The nearest neighbour network contains sections with small euclidean distances between the neighbours. The sections where there are small euclidean distances between neighbouring AcSs represent the clustering together of MUAPs from the same MU. The network is divided into clusters of AcSs.

If the number of AcSs in a cluster is above a set value, the average waveform of the cluster is found. Each large cluster contains the non-overlapping MUAPs from an active MU. Only non-overlapping MUAPs can be clustered using cluster analysis. Non-clustered AcSs are classed as superimposed waveforms. The statistics of the firing times of each MU cluster are calculated.

DECOMPOSITION OF SUPERIMPOSED WAVEFORMS

At high force levels only a few non-overlapping MUAPs exist. Therefore, the information gained from the last stage may not be sufficient to allow a clinician to make a diagnosis. To validate the results of the MUAP classification, superimposed waveforms containing overlapping MUAPs are decomposed into their constituent MUAP waveforms to extend the information already collected.

The decomposition of superimposed waveforms is divided into two sections: procedural and knowledge based analyses.

Procedural analysis - The procedural analysis is split into two sub-sections: -

Combination reduction - This first stage finds a reduced set of possible MUAP combinations that could form a superimposed waveform. The method uses the fact that MUAPs forming a superimposed waveform will have a total area sum equal to that of the superimposed waveform. The criteria used to select a MUAP combination as possibly forming a superimposed waveform is given below.

\[ |T_{Amc} - T_{Asw}| < \text{threshold} \]

where \( T_{Amc} \) = total area of a MUAP combination and \( T_{Asw} \) = total area of a superimposed waveform. Single MUAPs are still considered as possible waveforms that might form a superimposed waveform, as noise components may have prevented a detection earlier in the analysis. MUAP combinations selected from this stage are passed onto to the next optimisation stage.

Optimisation - This second stage of the procedural analysis further reduces the possible MUAP combinations forming a superimposed waveform selected from the first stage. The selected MUAP combinations from stage one are used in a template matching scheme (LeFever and DeLuca, 1982) with the superimposed waveform. The template matching scheme finds the residual error between a MUAP combination and the superimposed waveform by subtracting the MUAPs in the combination from the superimposed waveform. The subtraction is performed by aligning the maximum peak of the superimposed waveform with the maximum peak of one MUAP in the combination to form a residual waveform. This procedure is repeated on the residual waveform until all the MUAPs in a combination have been subtracted. If the final residual error is below a set threshold level, the MUAP combination is selected for the knowledge based analysis. To reduce errors when aligning MUAPs with a superimposed waveform, the order in which the MUAPs are subtracted from the superimposed waveform is changed and the subtraction repeated to find the smallest residual error of the MUAP combination.
Knowledge based analysis - The knowledge based analysis makes a final decision on which MUAPs are the most probable constituents of the superimposed waveform by studying how the firings of the candidate MUAPs fit in with the firing time statistics of the MUs. Each MUAP in a combination is given a degree of belief (or fuzzy value) and the fuzzy values are combined using fuzzy set theory. The expert system also gives an explanation of the conclusions formed when the user queries a solution.

The expert system, written in Prolog, consists of production rules in the knowledge base that are driven by an interpreter that incorporates uncertain reasoning. The knowledge based system contains both procedural and declarative knowledge representations of the EMG domain. The declarative rules contain a description of the relationships between the motor unit (MU) information collected by the classification of non-overlapping MUAPs and the superimposed waveforms being decomposed. The procedural rules interact with the declarative rules through rule attachments that activate demon procedures (Graham and Jones, 1988). The demon procedure computes fuzzy values for all the possible combinations of MUAPs that form a superimposed waveform. A more detailed description of the work is given in Loudon et al. (1990). The structure of the interpreter shell is derived from the work by Sehmi and Jones (1989).

RESULTS

The analysis method is being tested out on real and simulated myoelectric data. Figure 1 shows the classification results of a pathological EMG signal containing three MU trains.

FIGURE 1. The results of the decomposition of a pathological EMG signal recorded with needle electrodes.
The top section of Figure 1 shows the labelling of the MUAPs from the three MUs. The highlighted section indicates the classification of a superimposed waveform containing two overlapping MUAPs. The results can be queried by the user to see how the decisions were made. The lower section of Figure 1 shows the average MUAP shapes from the different MUs. The MUAP shapes and the general MU information aid the clinician in the diagnosis of the neuromuscular disorder.

**DISCUSSION**

The effectiveness of the numerical analysis and fuzzy reasoning structure of the expert system will only be determined through an extensive validation study. Pathophysiological models described in the form of *deep knowledge* would have to be included in the knowledge base of the expert system to extend the usefulness of this decomposition scheme in the actual diagnosis of neuromuscular disorders. Deep knowledge would enable the expert system to suggest a probable disease hypothesis and to suggest other tests that should be performed to support or refute that hypothesis.

**CONCLUSIONS**

The new analysis method can classify non-overlapping MUAPs and decompose superimposed waveforms containing overlapping MUAPs in an EMG signal at fairly high force levels in a time period that is clinically acceptable. The achievement of automatic classification of MUAPs at increased force levels will enable the collection of more MUAP information per test and therefore reduce the number of tests that have to be performed. This is of importance because the overall time required for a clinical examination is thereby reduced and the discomfort caused to the patient limited.

**Acknowledgements** - We wish to thank Dr. V.Brazinova (Leicester Royal Infirmary, U.K.) for her help in the provision of data and clinical advice and to acknowledge SERC and Medelec Ltd. for their financial support of Mr. G.H.Loudon.

**REFERENCES**

Appendix 4

Knowledge based decomposition of myoelectric signals

(presented at the IEE colloquium on Biomedical Applications of Digital Signal Processing, November 1989)
KNOWLEDGE BASED DECOMPOSITION OF MYOELECTRIC SIGNALS

G.H. Loudon, N.B. Jones, A.S. Sehmi

Abstract

This paper presents research relating to the use of computers for the intelligent decomposition of myoelectric signals. Digital filtering algorithms are used to reduce the noise in the signal. A normalisation and compression of the filtered signal is then performed to reduce the time of the analysis. The individual motor unit action potentials (MUAPs) in the myoelectric signal are identified using a pattern recognition method. The method uses features to describe the MUAPs in the myoelectric signal. Diagonal factor analysis is used to form uncorrelated factors from these features. The factors are then used in an adaptive clustering technique that groups together MUAPs from the same motor unit.

A method is proposed whereby the superimposed waveforms formed by a summation of overlapping MUAPs are decomposed using a knowledge based expert system. Initially, a template matching procedure is used to identify the possible MUAPs that make up the superimposed waveform. The motor unit firing times are then analysed by the expert system to decide which combination of MUAPs is most probable. Rules are used in the decision making of the system and are driven by an interpreter that incorporates uncertain reasoning based on fuzzy set theory.

Keywords - Electromyography, decomposition, signal processing, expert system, diagnosis.

1. Introduction

Muscle fibres are activated by impulses sent down motor nerves from the spinal cord. Each impulse causes a propagating wavefront in the muscle fibres connected to the associated motor nerve. The resultant waveform recorded at the detection site is known as the motor unit action potential (MUAP). The shape of the MUAP depends on the filtering properties of the electrode and its position relative to the muscle fibres. During a muscular contraction trains of impulses are sent down the motor nerves. The result recorded by the needle electrode, is a superposition of different MUAP trains and is known as the myoelectric signal (Basmajian, 1985). For a constant force contraction, the active motor units (MUs) fire at fairly regular intervals. The firing period distribution of a MU is almost gaussian with a very small variance (Andreassen and Rosenfalck, 1980).

The individual MUAP shapes in the myoelectric signal contain information that aids the diagnosis of neuromuscular disorders. Myoelectric data assessment by human experts involves a complex process of pattern recognition and a large part of this is performed mentally. One step in this process is the separation of the signal into its constituent MUAPs. The objective of the research work is to use a computer to perform the intelligent decomposition of a myoelectric signal into its constituent MUAPs at fairly high force levels. Furthermore, the computer provides a graphical interface to the user to simplify the interpretation of the findings. An analytical program written in the C language incorporating numerical algorithms and an expert system program written in Prolog are used to achieve these objectives.

Most automatic detection schemes are unable to find the MUAP constituents of a myoelectric signal at fairly high force levels due to the superposition of different MUAPs. The methods that can achieve decomposition of a myoelectric signal at these force levels take too long to produce the results to make them clinically useful. Also, they often require interaction with a human expert (LeFever and DeLuca, 1982).

This paper describes a new method for decomposing the myoelectric signal at fairly high force levels. The method can be split into two main sections: procedural (numerical) analysis and declarative (knowledge based) decomposition of superimposed waveforms.

2. Procedural analysis of myoelectric signals

The procedural analysis of a myoelectric signals finds candidate single MUAPs that exist in a signal and attempts to reduce the possible combinations of MUAP candidates that form a superimposed waveform. The procedural analysis has three sections: MUAP data collection, classification of non-overlapping MUAPs and numerical decomposition of superimposed waveforms.
2.1. MUAP data collection

A myoelectric signal contains noise due to needle movement, background activity from distant motor units and some instrumentation artifacts. The following three sub sections describe methods which help to discriminate useful signal from noise, thereby retaining information related to MUAPs near the electrode.

i) Filtering - A simple high pass filtering algorithm is used to eliminate any baseline drift and avoid the problem of electrode movement. It also suppresses any background activity picked up by the electrode. The simplicity of the design allows fast implementation. The filter used has a transfer function:

\[ H(z) = \frac{1 - z^{-1}}{1 - z^{-1}e^{-\omega T}} \] .......................... (1)

where \( \omega \) = frequency range of the myoelectric signal and \( T \) = sampling interval.

The high-pass filtered myoelectric signal is then smoothed using a five point triangular weighting function to filter out high frequency noise. The resulting signal is squared to enhance features for analysis in the following sub sections.

ii) Normalisation - The amplitude of the myoelectric signal recorded from person to person will vary dramatically. To avoid having to set trigger levels manually, a normalisation of the signal is performed. The ‘activity’ of the myoelectric signal is used as a measure for normalising the signal. The ‘activity’ of the signal is a measure of the variation of amplitude with time (Gerber and Studer, 1984).

\[ \text{activity} = \frac{1}{m} \sum_{i=1}^{m-1} |x_{i+1} - x_i| \] .......................... (2)

where \( x_i \) = magnitude of \( i^{th} \) sample and \( m \) = sample length of the study window.

The window is moved along the filtered signal recording the activity. The maximum activity of the signal is then compared with a fixed threshold value and the whole filtered signal scaled appropriately (Charles, 1988).

iii) Segmentation - To reduce data storage, only active data segments (AcSs) relating to local MUAPs are stored and used in further analysis. The filtered signal is split into AcSs using equation (2).

2.2. Classification of non-overlapping MUAPs

An unsupervised approach is used to classify non-overlapping MUAPs in the myoelectric signal.

i) AcS description - Eight shape descriptors derived from each AcS are used to classify the myoelectric waveforms. The use of shape descriptors dramatically reduces computational time. Examples of these descriptors are :- maximum peak to peak amplitude, number of turning points, total positive area. One problem is that the shape descriptors of each AcS may be correlated and may therefore provide limited information to discriminate between MU groups in certain data sets. Under these circumstances, some shape descriptors should not be used to make a classification decision.

Diagonal factor analysis (Gorsuch, 1974) is performed on the shape descriptors to find weightings (importance) for each. Diagonal factor analysis weights the descriptors such that they become uncorrelated and hence better at discrimination. The non ‘zero-weighted’ shape descriptors describing each AcS are used to form n orthogonal n-dimensional vectors in vector space in preparation for the cluster analysis.

ii) Cluster analysis - Cluster analysis (Tryon and Bailey, 1970) groups together AcS’s of similar shape. The euclidean distances between the vectors of the AcS’s are used to study how similar the shapes of the AcS’s are. The criterion used to decide if two AcS’s are derived from the same MU is :-

\[ \text{euclidean distance} < \text{threshold} \] .......................... (3)

The threshold value is calculated from the data set. This value will change with different data sets according to the tightness of the MU clusters. The threshold value is calculated by finding each AcS’s nearest neighbour and how the nearest neighbours are interconnected. The lengths of the nearest neighbour distances decides what value the threshold should be set at.
If the number of AcS's in a cluster is above a low set value, the average waveform of the group is made an initial template. The average waveform from each group is found using the actual waveform data and is used in the next section. Cluster analysis accommodates for the fact that the waveforms derived from one MU slowly change in shape over time. This can be achieved by comparing each new waveform with the last waveforms already discovered.

Only non-overlapping MUAPs can be clustered using cluster analysis. Non-clustered AcS's are classed as superimposed waveforms. The statistics of the firing times of each cluster are calculated. The firing period information from a MU cluster could be represented as a histogram as shown in figure 1. Unclassified MUAPs due to superpositions produce varying firing periods. The mean and standard deviation of the firing periods of each MU cluster are calculated using only the information from the classified MUAPs. The similarity of the mean firing period and the average waveform between MU clusters is used to decide if more than one cluster has been formed for one MU. Multiple clusters forming one MU are merged to form one MU cluster.

2.3. Procedural decomposition of superimposed waveforms

The method described here finds a reduced set of possible combinations of MUAPs capable of forming each superimposed waveform. The average MUAP templates calculated from the last section are used in the analysis. Only superpositions containing up to three MUAPs can be successfully decomposed. Decomposing superimposed waveforms containing more than three MUAP constituents would dramatically increase computational time and is therefore not attempted. The algorithmic decomposition is split into two parts.

i) Combination reduction - The MUAPs that make up a superimposed waveform will have a total area sum equal to that of the superimposed waveform. Therefore, to reduce the possible combinations of MUAPs that could make up a superimposed waveform, the difference between the MUAP combinations areas and the superimposed waveform area is studied. At this stage, single MUAPs still need to be considered, as noise components may have prevented a detection earlier in the analysis. If the error is below a certain threshold, the combination is used in the next part. The level of the threshold is related to the size of the threshold in the cluster analysis.

ii) Optimisation - The MUAP combinations selected from the first part are used in a template matching scheme with the superimposed waveform. The template matching procedure (LeFever and DeLuca, 1982) finds the residual error between a MUAP combination and the superimposed waveform by subtracting each MUAP in the combination from the superimposed waveform. The subtraction is performed by aligning the maximum peak of the superimposed waveform with the maximum peak of one MUAP in the combination and forming a residual waveform. This procedure is repeated on the residual waveform until all the MUAPs in a combination have been subtracted. If the final residual error is below a certain threshold, the combination is used in the next section. Again, the threshold level is related to the size of the threshold in the cluster analysis.

3. Knowledge based decomposition of superimposed waveforms

The numerical analysis suggests possible MUAP combinations that might form a particular superimposed waveform. Errors in results will occur more often if only traditional analytical methods were used in the decomposition process. These could be due to noise in the signal or the similarity between residual errors resulting from different MUAP combinations. A human expert is able to identify which of the possible MUAP combinations comprise the superimposed waveform, by studying the firing times of the MU trains. He/she would arrive at a decision based upon uncertain and incomplete evidence available from the MU firings.

To contend with problems associated with decomposition of superimposed waveforms, an expert system is being designed which uses a fuzzy certainty reasoning model. Our expert system categories the representation of knowledge into domain and control knowledge.

The expert system analyses the possible MUAP combinations forming a superimposed waveform and decides which combination is most probable. This is achieved by studying how the firings of the candidate MUAPs fit in with the firing time statistics of the MUs. Each MUAP in a combination is
given a degree of belief (or fuzzy value) and the fuzzy values are combined using fuzzy set theory (Zadeh, 1965). Bayesian theory was not used because the method requires prior probability functions to be specified for the MUAP combinations. It also assumes independence between the MUs.

The expert system gives an explanation of the results by displaying the rules used in the analysis. The expert system can be split into three main sections: the data base, the knowledge base and the inference engine.

3.1. The Fuzzy Procedural Model (Data base)

The data base contains information on the possible combinations of MUAPs that constitute superimposed waveforms, and also on the smallest firing periods (SFPs) between each superimposed waveform and the nearest neighbouring MUAP (figure 3). Each MUAP candidate is given a fuzzy value (for each superimposed waveform) according to the ‘possibility’ of a MUAP occurring at the position of the superimposed waveform.

The fuzzy membership value of each MUAP candidate is calculated using a ‘demon’ procedure which maps the SFP for that MUAPT onto a fuzzy membership function (μx) (which represents the distribution describing the statistics of MU firing periods, see figure 2). A fuzzy value of 1.0 (true) is given to a MUAP candidate when the SFP equals the mean firing period of the MU. A fuzzy value of 0.0 (false) is given to the MUAP candidate when the SFP occurs outside the limits of μx.

3.2 The Fuzzy Declarative Model (Knowledge base)

This model attempts to capture the decision making processes used to decompose a superimposed waveform with a set of fuzzy rules (or productions). The rules in the knowledge base cater for problems associated with unclassified MUAPs which can cause the SFP to be greater than that expected (see figure 3). This is achieved by repeating the distribution describing MU firing periods at multiples of the mean firing period.

The overall fuzzy value of each candidate MUAP combination (Z) in a superimposed waveform is calculated using the formula:

\[ F(Z) = F(X) \times \text{NOT}(F(Y)) \]

where \( F(Z) \) is the overall fuzzy value of a MUAP combination, \( F(X) \) is the combined fuzzy value of the intersecting set of individual MUAPs in a combination and \( \text{NOT}(F(Y)) \) is the combined fuzzy value of the exclusive set of individual MUAPs in a combination. Fuzzy set theory is used to find the combined fuzzy values from the logical relationships AND, OR and NOT. For AND, the minimum fuzzy value is taken. For OR, the maximum fuzzy value is taken and for NOT the fuzzy value is negated.

\[ F_{\text{AND}} = \min(F1 \text{ AND } F2 \text{ AND } F3 \text{ AND } F4 \text{ .... }) \equiv F(X) \]

\[ F_{\text{OR}} = \max(F1 \text{ OR } F2 \text{ OR } F3 \text{ OR } F4 \text{ .... }) \equiv F(Y) \]

\[ F_{\text{NOT}} = 1 - F \]

3.3 The inference engine

The inference engine is backward chaining and provides explanation capabilities for the declarative model described above. It also provides the interfacing with the data base through the use of the ‘demon’ procedures. The inference engine performs a search of the knowledge base until it finds a rule with matching premises. The rule is ‘fired’ and the fuzzy values of the rule premise are combined (using equation 5). The new fact derived from the rule conclusion is asserted into the data base. Once the rule has been used it is not used again in the same search. The procedure of searching for rules and propagation of fuzzy values is repeated until no more matching rules can be found, or a solution has been reached.

The expert system allows the user to examine how a particular MUAP combination was chosen. The explanation shows the rules used in the analysis. The expert system will also list other candidate MUAP combinations in descending order of their combined fuzzy values.
4. Discussion

The procedural decomposition method is being tested on simulated and real data for different data sets and different levels of noise. The expert system is still in the development stage. Some of the ideas of the expert system have been tried out using a procedural analysis to test the validity of the approach. The procedural method has been able to decompose simulated signals into their individual MU trains.

Figure 4 shows a simulated myoelectric signal containing four MU trains. The signal simulates a myoelectric signal recorded from a muscle using needle electrodes. The results of the decomposition are shown in figure 5. Information about one of the four different MUAP shapes classified is shown. Both the individual and superimposed waveforms are classified correctly. Figure 6 is an example of information given about one of the queried superimposed waveform results.

The next stage of the research is to complete the development of the expert system and to test the whole system on real and simulated data. The effectiveness of the fuzzy reasoning mechanism of the expert system will be determined through an extensive validation study. ‘Deep knowledge’ in the form of pathophysiological models would have to be included to extend the usefulness of this knowledge based decomposition scheme in the diagnosis of neuromuscular disorders.

5. References

Figure 1. Histogram of the MU firing periods.

Figure 2. The distribution describing the MU firing periods.

Figure 3. The firing times of an active MU.
Figure 4. A simulated myoelectric signal containing four MUs.

Figure 5. Results of the MUAP classification.

Figure 6. Information on a queried superimposed waveform.
Appendix 5

A set of classification techniques for the extraction of non-periodic transients from noise: an application in electromyography.

(submitted for publication in the IEE Proceedings, Part A)
A set of classification techniques for the extraction of non-periodic transients from noise: an application in electromyography

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Abstract

This paper describes a new set of techniques for the extraction and classification of transients in a general background of other signals and noise. An example of its use in electromyography is described. The automatic signal-processing method classifies non-overlapping transients from different sources into groups of closely similar shapes using a pattern recognition method. Each transient is described by a set of features to form uncorrelated factors which are then used in an adaptive clustering technique to group together transients from the same source. In particular, motor unit action potentials in a myoelectric signal can be classified into their motor unit groups using this method.

1 Introduction

Many complex signals contain repeating transients of interest within a general background clutter of unwanted components and measurement noise. If the transients of interest occur at predictable times and yet are uncorrelated with the rest of the signal, the required information can be extracted by signal averaging. The problem under consideration here is that which arises when the initiation of each transient in the signal is to some degree unpredictable and so signal averaging is not an available option. In addition it is assumed to be necessary to discriminate between transients of several classes. Each member of a particular class is assumed to be similar to all the others but not identical.

The paper describes a set of classification techniques for use in this situation and is limited to the case where the transients of interest do not overlap to any significant extent. The research presented here is however only part of more extensive work on signals in which the important components can overlap each other, thus involving a form of interference. The methods discussed here have been found to be useful in this more general case as well if used in conjunction with other techniques for resolving ambiguities arising from the interference of one wave with another (Loudon et al., 1990). These complications are not discussed in this paper and attention is concentrated upon the essential elements of the extraction and classification process.

The primary field from which this work arose was electromyography. In this the electrical activity of muscle (the EMG) is to be analysed so that the individual transient components known as Motor Unit Action Potentials (MUAPs) are extracted from the signal and presented to the clinician for diagnostic purposes. The objective of the process is to separate out the MUAPs arising from the several motor units (MUs) which are contributing to the measured EMG, and group them according to their source motor unit in the face of shape variation. Alongside the general principle of the process described, an example is presented from the field of electromyography.

The steps in this process, described below, are:

1. Feature description.
2. Diagonal factor analysis.
3. The formation of a "nearest neighbour network".
4. Clustering.

2 Transient classification

The analysis method initially extracts the areas of activity containing the transient waveforms from the background signal. Loudon et al. (1989) describes the procedure in more detail. Each area of activity is known as an active segment (AcS). The top section of Fig.1 shows an EMG signal recorded with a needle electrode. The bottom section shows the active segments (containing the MUAP waveforms) that have been extracted from the signal. The classification technique which follows this pre processing is split into four stages as is described below.
Fig. [1]. The extraction of MUAP activity from a myoelectric signal.
2.1 Feature description

Every active segment formed is described by a set of features. In the example under discussion eight features are shown. A relatively large number of features are used so that a fairly complete description of each active segment can be made. The eight features of each active segment are used to classify an active segment into an appropriate group. The use of a large number of features allows discrimination between similar active segment shapes containing transients from different sources, thus avoiding the problems encountered by previous methods (Mishelevich, 1970). The use of features instead of the actual data samples of an active segment dramatically reduces computational time. The eight features used are given below:

1. Maximum peak to peak amplitude.
2. Maximum positive peak amplitude.
3. Maximum positive slope.
4. Maximum negative slope.
5. Number of turning points.
6. Total positive area.
7. Total negative area.
8. Total number of samples.

The number of turning points (TPs) in an active segment refers only to the significant peaks in a segment. Small peaks arising from noise in the signal are not included.

One of the problems with using features to represent an active segment is that the features may be correlated with each other. Some of the correlated features may therefore be given too much importance in the classification while providing limited extra information thereby producing less accurate results overall. For this reason Andreassen states that 'no two features carrying almost the same information should be included in the feature vector' (1978). Under these circumstances some of the features should not be used to make a classification decision. Diagonal factor analysis is used to resolve this problem.

2.2 Diagonal factor analysis

The method of diagonal factor analysis (Gorsuch, 1974) is performed on the features of all the active segments in conjunction with Hunter analysis (Hunter, 1972) to find the weightings (importance) for each feature. Diagonal factor analysis finds new features (orthogonal factors) which are uncorrelated, thereby avoiding the problem mentioned earlier. The diagonal factor analysis procedure is described below.

Firstly, the correlation matrix is formed from the original eight features. Correlation measures the association between two variables. Pearson's product moment correlation coefficient (\( \rho \)) is used as the parametric measure of linear association between two variables \( X_1 \) and \( X_2 \). It is defined as the ratio of the covariance between two variables to the square root of the product of the two variances (\( \sigma_1^2 \), \( \sigma_2^2 \)) (King and Julstrom, 1982). Thus

\[
\rho_{12} = \frac{\text{Cov}(X_1, X_2)}{\sigma_1 \cdot \sigma_2} = \frac{\text{Cov}(X_1, X_2)}{\sigma_1^2 \cdot \sigma_2^2} \quad \ldots \ldots \ldots \ldots \ldots \ldots \ldots (1)
\]

For sampled data, an unbiased estimate, \( r_{12} \), of the correlation coefficient is:

\[
r_{12} = \frac{N\sum(X_1X_2) - \sum X_1 \cdot \sum X_2}{(N\sum X_1^2 - (\sum X_1)^2) \cdot (N\sum X_2^2 - (\sum X_2)^2))^{1/2}} \quad \ldots \ldots \ldots \ldots \ldots \ldots \ldots (2)
\]
where $X_1$ and $X_2$ are the numerical values of two features and $N$ is the number of active segments. $\sum X_1$, for example, is the summation of the numerical value of the feature $X_1$ from $N$ active segments. The coefficients $r$ vary from +1.0 (perfect positive correlation) through to zero (no correlation) to -1.0 (perfect negative correlation).

Next, the sum of squared correlations for each column of the correlation matrix is found. The sum of squared correlations with the other features indicates how much of the other features can be predicted from a diagonal factor defined by the feature associated with a particular column. The feature with the highest sum of squared correlations with the other features is selected. The selected feature defines the first diagonal factor and is the feature which carries most information about the other features. The weighting given to the first diagonal factor is the square root of the associated auto covariance (unity). Fig.[2a] shows the column with the highest sum of squared correlations and the first diagonal factor (highlighted with a box). The effect of the first diagonal factor is then eliminated from the correlation matrix to form the residual matrix (see Fig.[2b]) according to equation (3) given below.

$$R_{ij,A} = R_{ij} - P_i \cdot P_j$$

where $R_{ij,A}$ is the $ij^{th}$ correlation value of the residual matrix, $R_{ij}$ is the $ij^{th}$ correlation value of the original correlation matrix and $P_i$ and $P_j$ are the weightings given to the $i^{th}$ and $j^{th}$ feature. The equation used to calculate $P_k$ associated with the elimination of the effect of feature $v$ is given below.

$$P_k = \frac{R_{vk}}{(R_{vv})^{1/2}}$$

where $P_k$ is the weighting of the $k^{th}$ feature, $R_{vk}$ is the $k^{th}$ value in the row $v$ containing the first diagonal factor of the original correlation matrix and $R_{vv}$ is the value of the selected feature used as the first diagonal factor.

The sum of the squared correlations for each column of the residual matrix is then found and following the above procedure, the second diagonal factor calculated (Hunter, 1972). The procedure is repeated until the weighting of the factors is below a value of 0.1. There are then $n$ factors in place of the original eight features, where $n < 8$. The weighted features (or orthogonal factors) describing each active segment are used to form a vector in a $n$-dimensional vector space in preparation for the clustering of the active segments.

### 2.3 Nearest neighbour network

The $n$-dimensional vector describing an active segment is used to represent the shape of the waveform in that active segment. The next stage of the analysis involves forming a network connecting all the active segments together (after Tryon, 1970).

The active segments are connected in a sequence according to the similarity of the vectors representing the shapes of the active segments. The euclidean distance (ED) between two vectors representing two active segments is the measure used to study this similarity.

$$ED_{xy} = \left( (x_1 - y_1)^2 + (x_2 - y_2)^2 + (x_3 - y_3)^2 + \ldots \right)^{1/2}$$

where $x_i$ are the orthogonal coordinates of one active segment under consideration and $y_i$ are the orthogonal coordinates of the other active segment under consideration. The euclidean distances between all the active segments are calculated. The active segments that are most similar are connected together. The minimum of all the euclidean distances is found and the two active segments defining that distance are recorded. Next, the smaller magnitude of these two vectors is calculated. The nearest neighbour distance is then the minimum euclidean distance divided by the smaller of the two vector magnitudes.

$$NN_k = \frac{\min (ED_{xy})}{\left( x_1^2 + x_2^2 + x_3^2 + \ldots \right)^{1/2}}$$
The feature correlation matrix formed from all the active segments.

Fig.[2a].

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<td>-0.32</td>
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<td>7</td>
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<td>-0.90</td>
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The residual matrix of the active segments.

Fig.[2b].

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<td>-0.10</td>
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During the formation of a network, the search for the nearest neighbour of an active segment (which is part of the network) can only involve active segments not already in the network. Fig. [3] shows the formation of a nearest neighbour network from active segments extracted from an EMG signal containing four MUs. Active segments containing non-overlapping MUAPs from the same MU are grouped together.

The method has the ability to group together MUAPs from the same MU, thus allowing for the fact that MUAPs gradually change in shape over time due to electrode movement. The method also caters for situations in diseased states when the variability of the MUAP shapes from a MU is much larger than for a normal case for pathophysiological reasons.

2.4 Clustering

The next stage of the classification process is to use the nearest neighbour network information to form groups of active segments, where each group contains non-overlapping transients from the same source. To do this the network must be divided into clusters. Fig. [4] shows the nearest neighbour distances of the network formed from Fig. [3]. The network is cut where the nearest neighbour distance increases abruptly, thus forming groups of active segments (see Fig. [3]). This is achieved by normalising the distances (with the maximum distance being 1.0) and studying the variation in the nearest neighbour distances of the network. The algorithm used, searches for nearest neighbour distances in the network that are significantly larger than the average and which occur at positive turning points on the nearest neighbour distance network shown in Fig. [4]. The smallest distance found from the search is then used as the threshold level for splitting the network into groups. The average waveform of each group is made an initial template for the transient in question and is calculated using the actual data samples of the active segments rather than the features.

3 Results of applying the method to the EMG signal

Fig. [5] shows the results after the classification of the non-overlapping MUAPs. The top section of the results shows the EMG signal with labels, corresponding to the positions where the MUAPs from the different MUs were located. Below, are pictures of the averaged MUAP shapes from the different MUs and the statistical information describing the size of the average MUAPs, the numbers found and the MU firing times. The average MUAP shape of each MU was formed from the actual waveform data points using median averaging. Fig. [6] shows the overprinting of MUAP waveforms from the same MU. All the MUAPs in the signal were correctly classified into their MU groups, even when MUAP4 showed a large variation in shape during the EMG recording, because of disease and when there was a high degree of similarity in shape between MUAPs 1, 2 and 3.

4 Summary, Conclusion and Comment

The use of features to describe transients in conjunction with diagonal factor analysis provides a new method for the classification of non-overlapping transients embedded in background noise. The method is directed towards overcoming problems associated with the accurate classification of MUAPs in EMG signals and the associated speed of implementation. The methods described are of general interest in the analysis of repeating transients but have been shown, via an example presented here, to be particularly useful in electromyography. More research has been carried out in the area of decomposition of interference EMGs and is described in Loudon et al. (1990).

5 References


Fig.[3]. The nearest neighbour network formation of the myoelectric signal.

Fig.[4]. The nearest neighbour distances of the myoelectric signal.
Fig. [5]. The results of the MUAP classification method.
Fig. [6]. The overprinting of the MUAPs from the four MUs.


Appendix 6

Knowledge-Based Systems in Neuroelectric Signal Processing and interpretation

(submitted for publication in the IEE Proceedings, Part A)
Knowledge-Based Systems in Neuroelectric Signal Processing and Interpretation

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Abstract

This paper describes expert systems for decision support in the interpretation of brainstem auditory evoked potentials (BAEP), decomposition of interference pattern electromyograms (EMG) and analysis of sleep electroencephalographs (EEG). The former two systems are the work of the authors' and the latter system due to Jansen and Dawant (1989) is reviewed here for completeness and to help appreciate the wide application of knowledge-based signal processing techniques in neuroelectric signal analysis and interpretation. These systems are characterised by a significant amount of coupling between numerical and symbolic processing techniques. The BAEP and EMG expert systems incorporate rule-based inference mechanisms with a high degree of uncertain inference using fuzzy logic. Both these systems are coded in the C language for numerical processing and tokenisation of raw data and in Prolog for intermediate symbolic processing stages. The EEG expert system uses an object-oriented approach to capture high level stereotypes of spatio-temporal concepts in multi-channel EEG signals. These stereotypes can trigger lower-level numerical procedures in an opportunistic manner to extract contextual numerical information. This system uses a limited form of uncertain inference and is coded in the KEE knowledge engineering environment and in Lisp.

A conceptual hardware and software framework for implementing such expert systems and related support environments will also be described briefly. Research and development work on the feasibility of this framework is underway and is based upon modern digital and graphics signal processing devices and a blackboard expert system model to enable real-time distributed knowledge-based signal processing.

1. Introduction

The manual assessment of neuroelectric data by human experts is based upon complex processes of data reduction and feature extraction, some of which are apparently subjective. The complete task of data evaluation and interpretation falls largely on the human expert who uses an holistic view of the data collected, in conjunction with some simple quantitative measures which can be calculated by computer-based algorithms. Since the goals of the knowledge-based systems described in this paper are to automatically analyse and interpret the appropriate neuroelectric signal in a computer, the holistic reasoning that a human expert uses must be simulated. The simulation of this reasoning is performed using knowledge-based expert system techniques which are coupled to varying degrees of abstraction with their numerical analysis counterparts. There are three domains in which the knowledge-based systems we describe function. These are:

- (i) Interpretation of Brainstem Auditory Evoked Potentials (BAEP),
- (ii) Decomposition and analysis of Interference Pattern Electromyograms (IPEMG),
- (iii) Analysis of Sleep Electroencephalograph (EEG).

1.1 Brainstem Auditory Evoked Potentials

Sensory stimulation of the peripheral nervous system will, under normal circumstances, result in changes to the on-going activity of the central nervous system. These variations are known as evoked potentials. Some EPs can often be seen as a wave or group of waves in the electroencephalogram (EEG). Most EPs however, are indistinguishable in routine EEG recordings because of their inordinately low amplitudes (0.1 to 2µV) and the interference of background cerebral electrical activity and electromyographic (EMG) artifacts (Chiappa and Roper, 1982).
By exploiting the non-stationary time locked nature of an evoked potential with its related stimulus and assuming that background EEG activity is a stationary random noise process, simple synchronous averaging of the single-responses can be used to extract the EP. The features of the electric potentials (waves) in the averaged EP brought out in this way are used in the assessment of neurological condition as each wave is assumed to be generated by a specific sub-cortical structure. The presence or absence of the appropriate EP waves and their latencies are the primary characteristics used in clinical interpretation.

The KBS described in this paper scores (or labels) the brainstem auditory evoked potential (BAEP). This is morphologically perhaps the most complex of the clinically useful EPs. Single BAEP responses are of very low amplitude and signal to noise ratio (< -20dB). A numerical data reduction algorithm has been developed (Sehmi, 1988b) that performs well even under these circumstances. Hence, it is possible to incorporate the output from it into the reasoning strategy that labels BAEP components.

For a more detailed discussion of the physiology and use of BAEPs, the reader is referred to Chiappa and Roper (1982). A description of the adaptive data reduction algorithm mentioned above (which is also called Event Analysis) can be found in Sehmi (1988b) and Sehmi et al. (1988c).

1.2 Interference Pattern Electromyograms

The electrical activity recorded from a muscle when under contraction is known as the myoelectric or EMG signal. The myoelectric signal results from the activation of groups of muscle fibres by impulses sent down motor nerves from the spinal cord. Each nerve impulse innervates a group of muscle fibres known as a motor unit (MU). The resultant waveform recorded from a MU is known as the motor unit action potential (MUAP) (Basmajian and DeLuca, 1985). During a constant force contraction, trains of impulses are sent down the motor nerves at fairly regular intervals resulting in a train of MUAPs. The firing period distribution of nerve impulses is almost gaussian with a very small variance (Andreassen and Rosenfalck, 1980). The resultant myoelectric signal recorded with needle or surface electrodes is then a summation of the individual MUAP trains from different MUs in the muscle. The signal is called the interference pattern EMG (IPEMG).

The shapes of the MUAPs and some global characteristics of an EMG signal (for example amplitude of the envelope, level of activity etc.) at both high and low contraction levels contain important diagnostic information. Clinical diagnosis of neuromuscular diseases is a time consuming process that requires a highly skilled operator to analyse the EMG data and to make diagnostic decisions. The operator performs a visual interpretation of the EMG data and therefore has to study tests at low contraction levels where the individual MUAPs are easily distinguished.

The objective of the EMG expert system is to intelligently decompose the IPEMG into its individual MUAP trains under fairly high force level conditions (say 30% maximum voluntary contraction). This requires the classification of both non-overlapping MUAPs and the decomposed superimposed waveforms formed from overlapping MUAPs in the signal. Non-overlapping MUAPs are classified using a statistical pattern recognition method. The method first describes the MUAPs by a set of features and then uses diagonal factor analysis to form uncorrelated factors from these features (Gorsuch, 1974). An adaptive clustering technique groups together MUAPs from the same MU using the uncorrelated factors (Tryon, 1970).

The decomposition of superimposed waveforms is divided into two sections. The first section is a procedural method that finds a reduced set of all possible combinations of MUAPs which are capable of forming each superimposed waveform by using a template matching procedure. A more detailed description of this procedural analysis can be found in Loudon et al. (1989). The second section is the knowledge-based analysis of the candidate MUAP combinations forming each superimposed waveform (Loudon et al., 1990). This latter analysis decides which combination is the most probable.

There exist methods to decompose a superimposed waveform into its constituent MUAPs. However, with current methods of decomposition either errors will result, the time taken for decomposition is very long (LeFever and DeLuca, 1982) or much training is required to use the decomposition scheme. Errors could be due to noise in the signal or because of the similarity between results after a pattern matching analysis. Human experts are able to identify which of the possible MUAP combinations comprise a superimposed waveform by studying the firing times of the MUAP trains (Basmajian and DeLuca, 1985).
Typically they would arrive at a decision based on uncertain and incomplete evidence available from the MU firings already classified. This observation has led to the specification of the EMG expert system which performs the decomposition protocol of superimposed waveforms.

### 1.3 Sleep Electroencephalograms

Techniques developed to record and score EEG sleep states have found application in neurology, psychiatry, psychology, animal behaviour and human physiology. Early work by Loomis et al. (1937) established a convention of six sleep stages which are classified by a combination of, and relationships between, waveform patterns observable in the multiple EEG channels. The features in these patterns are due to delta waves, K complexes, theta, alpha, sigma and beta spindles in the EEG channels. In addition to the six sleep stage activities, rapid eye movement from the electro-oculogram (EOG) and EMG are also of interest and measured when available.

To classify EEG segments into a particular sleep stage, a certain amount of heuristics must be employed. A human scorer would use a combination of rules involving EEG and EOG waveforms and the EMG level to decide which is the sleep stage for a given segment of EEG data. The process of sleep staging has become so successful in the study of sleep, that quantitative psychophysiological measures are now used to define sleep stages rather than to merely describe them (Empson, 1986).

The automation of sleep staging has therefore attracted much research effort. The need to analyse single channels of EEG data in the context of the activity seen in the other channels has been known by workers in the field, but never attempted. The EEG expert system due to Jansen and Dawant (1989) shows that successful sleep staging can be performed with a knowledge-based system which incorporates contextual information, and that their technique will prove useful for clinical practice.

### 2. Numerical and Symbolic Coupling in Knowledge-Based Systems

This section describes the concept of coupled systems and the associated knowledge representation, control of reasoning and heuristic reasoning strategies that can be incorporated into such systems.

The terms expert systems (ES) and knowledge-based systems (KBS) are commonly used to describe subfields of artificial intelligence (AI) that concern the emulation of human problem solving methods within restricted domains of specialisation. A KBS is more precisely described as a system that incorporates AI programming methodologies and does not attempt to mimic expert behaviour, but instead uses heuristics to surmount numerical limitations that may be encountered. Knowledge-based signal processing schemes in general employ a strong coupling between numerical and symbolic processing. The coupling is bi-directional and the emphasis placed in the one or the other mode of processing is dependent upon the requirements of the analysis at hand.

In the first instance, when numerical processing becomes intractable and/or weak then knowledge-based techniques are incorporated to overcome the difficulties. The difficulties are manifested in terms of a requirement for more realistic models of the problem domain, increased support for novice users and a need to incorporate heuristics in the search for information in the data being analysed. The advantages of coupling KB techniques with numerical methods to overcome numerical processing difficulties has been widely recognised in the area of signal interpretation and classification.

When used on their own, symbolic processing techniques break down if attempts are made to reason about time-varying phenomena and if predictions are to be made on the behaviour of complex probabilistic systems (Widman et al., 1989). These limitations result in expert systems under-performing in applications such as planning, diagnosis and advice-giving. These applications require a deeper, flexible and more robust understanding and knowledge of the behaviour of realistically complex problems. So, in the second instance, a coupling of symbolic methods with numerical procedures to enhance knowledge about behaviour is more appropriate in a complex model-based simulation scheme than in a complex signal processing and interpretation scheme.

The BAEP and EMG expert systems described in this paper lean more towards the first type of numerical and symbolic processing coupling. It is a form of coupling which uses shallow knowledge since there is no causal (i.e. model-based) representation of the generation process of the signals being
analysed. The EEG expert system leans more towards the second type of coupling since a contextual model of spatio-temporal relationships in the EEG signal is maintained. This type of coupling is often thought of as using deep knowledge.

A KBS will often function within an ill-structured domain. This is because the raw data and knowledge of how to use this data is incomplete, uncertain, noisy and/or conflicting. The numerical algorithms needed to solve complex problems in these domains cannot be stated explicitly and so a coupling with symbolic processing is attempted to surmount these problems. Under certain circumstances AI problem-solving methods are useful simply because of the need to represent both contextual and numerical information in a decision tree structure that is easily maintained and extendible. The ability to easily define and manipulate expressive data structures in a symbolic processing scheme is ideal for representing contextual models (i.e. the spatial and temporal relationships that exist between features) in multi-dimensional neuroelectric data.

In addition to the benefits of having access to high-level data modelling and representation structures, symbolic processing methods enable one to use these same data structures for explaining and justifying the reasoning behind the solutions obtained. Since a logic similar to that which a human expert uses is followed, it is possible to list the partial conclusions, the potential candidate solutions, the failed avenues of search and the full reasoning process followed up to the most current conclusion made - including the final solution; which is the interpretation of the signal being analysed.

2.1 Knowledge Representation and the Control of Inference

The type of knowledge representation method used for representing expert knowledge is a central consideration for expert systems. It not only determines the ease with which concepts for inference are laid out, but it also has implications in the design of the inference engine that controls the reasoning process using the knowledge-base. There are two main methods of knowledge representation: production rules and frames (objects), and within each of these representation schemes two control mechanisms are commonly applied: forward and backward chaining.

2.1.1 Production Rule-Based Knowledge Representation

Production rule knowledge representation schemes (Post, 1943) use structured condition-conclusion pairs. These pairs are intended to capture knowledge for strategic, tactical, descriptive and quantitative use in concise modular units. The condition part comprises data which can be obtained from either the user, persistent or dynamic databases, the activation of low level analytical or measurement procedures or the intermediate conclusions reached by other rules. The conclusion part comprises intermediate solutions or one of possibly many final solutions.

Since most real-world applications contain some non-deterministic characteristics, one usually associates a degree of confidence with the condition-conclusion pairs. The confidence values are indicators of the belief the knowledge-base designer has in the conclusion being valid when the conditions are true. Therefore the conditions of intermediate conclusions can (indirectly) also be made imprecise. Conditions containing data derived from low level analytical or measurement procedures are often provided with imprecise attachments which express their individual degrees of reliability. The BAEP and EMG expert systems perform this latter function using fuzzy logic model representations of the raw data in their respective domains.

The simplicity of the production rule structure is its main advantage. Knowledge can be made modular, homogeneous and, in some domains, it can be expressed in a way that lends itself to a very natural (though simplistic) way of reasoning. Production rules are adequate for modelling shallow reasoning processes. The problem with this scheme is that the rule ordering can become important, and therefore potentially disastrous for the global semantic interpretation of the knowledge base. Often great care is taken to avoid this order-dependency by including additional guarding propositions in the list of conditions in the rule. This reduces the overall efficiency of the system and because it is logically superfluous, explanations can become opaque. In addition, the maintenance and expansion of the knowledge-base can also become difficult.
2.1.2 Frame-Based Knowledge Representation

Frame structures (Minsky, 1975) are the precursors to those structured objects now widely used in, and sometimes wrongly believed to originate from, object-oriented programming techniques. Knowledge representation in frames is achieved through value, procedure and/or rule attachments to frame slots. In the context of signal processing frames represent concepts such as a specific feature and/or a class of features in a waveform. The slot names are the attribute names of that feature being represented (e.g. duration, number of phases, latency of peak, power content in a frequency band, etc.). Procedures are activated to obtain values for the attributes. In a way similar to the production rules above, these procedures may prompt the user, examine a database, invoke low-level procedures or activate other frames. A successfully activated frame results in some hypothesis being asserted and this implies that the assertion of slot values has also been made successfully. Hence, when compared with production rules, the assertion of slot values is equivalent to the assertion of conditions and the assertion of an hypothesis is equivalent to the assertion of a conclusion.

Thus a frame can be viewed as a super-set of production rules, and indeed some have argued that there is no difference at all in the two schemes (Hayes, 1979). However, addition of extra (e.g. control) slots in the frame to hold, say, lists of confirmed or denied value assertions, pointers to other frames to be considered if the current frame is unsuccessfully activated, confidence factors, measures of importance, simple data and/or default slot values makes the frame representation a more powerful tool in modelling existing structure in domain knowledge. In this way frames can be used for modelling deep reasoning processes, and in those cases where the frame and production rule schemes are logically equivalent, it does not follow that important considerations like readability and expressive power will also be equivalent (Ringland, 1989).

The slots which hold pointers to other frames allow hierarchical model taxonomies of the problem domain to be constructed. This permits implementation of both context for expecting and interpreting new data and of simplification in the control mechanism. We have seen that an element of context sensitivity can be introduced. It follows therefore that a frame-based expert system can be more efficient than a production rule-based system because information is gathered only at the time of frame activations. These activations can in turn invoke procedural processes or activation of other frames. The use of context therefore causes the system behaviour to become opportunistic with the additional benefits of efficiency and focus of attention. This type of behaviour can be harnessed in a knowledge-based signal processing scheme so that quantitative numerical information is extracted only when needed. The subsequent transformation of this numerical data into token symbols for use by higher level frames in a hierarchy is hence, by implication, also performed on a demand-driven basis. The expert system due to Jansen and Dawant uses frames in the way just described to perform knowledge-based EEG analysis.

2.1.3 Control in Production Rule-Based Systems

Expert systems exhibit a distinct separation of knowledge from control of reasoning using that knowledge. It is therefore possible to utilise different control or inferencing methods to solve problems without affecting the structure of the knowledge-base. The main control mechanisms are forward and backward chaining. Both can be understood by visualising the directed graph (state-space) containing the low-level data at leaf-nodes and the solution at the root node. Intermediate solutions are held in the remaining nodes of the directed graph. The entire state-space is implicitly defined by the lists of conditions and conclusions in the knowledge representation used.

To perform forward chaining in a production system the rules are examined to see if their conditions match initial data contained in the leaf nodes of the state-space. A successful match will trigger the corresponding rule thereby adding conclusions to a dynamic database and moving the search to intermediate nodes in the state-space. The initial data and the new conclusion are used to initiate a new cycle to recognise an applicable rule(s) which will in turn add another conclusion(s) to the dynamic database. The cycles continue until no more rules are applicable or the solution has been found at higher levels or the root of the state-space. Techniques exist to select the best rule in any one cycle and to prevent looping when the condition part of rules is referenced in its conclusion part.
Backward chaining is performed by first examining the rules that have conclusions which produce the
desired solution in the state-space. The conditions of these rules constitute the intermediate nodes in the
state-space. The rules which contain any of these conditions in their conclusion parts are then examined in
turn and so on until the leaf nodes in the state-space are reached or there are no more rules left.

Both control strategies can build a proof tree from the set of node traversals in the state-space
connecting the solution node to the initial data. This proof tree can be used to derive explanations of why
or how any intermediate conclusions were reached.

### 2.1.4 Control in Frame-Based Systems

Forward and backward chaining can be implemented in a frame-based system despite the apparent
complexity of the representation. In such a system control of reasoning is effected through an ordered set
of condition or conclusion assertions in an agenda. If an assertion is found to be valid, the assertions of
which it is suggestive are placed on the agenda in positions that reflect the degree of belief in the assertion
and the measure of suggestivity in the subsequent assertions. Complementary assertions can be placed on
the agenda in the event that the assertions are invalid. If an assertion cannot be evaluated because some
of its assumptions are unknown, then those assumptions are placed on the agenda in positions determined
by their measure of importance and the agenda level of the original assertion.

Aikins (1980, 1984) points out that since frames represent global concepts which are closer to a
human's logical interpretation of ideas, control of reasoning and explanations become more manageable
and understandable respectively.

Forward and backward chaining can be implemented in the frame representation by exploiting the
ordering of assertions in the agenda (Smith and Clayton, 1984). Goal-directed depth-first backward
chaining can be achieved by placing high-level goals (assertions) and subgoals (which suggest the
high-level assertion) at the top of the agenda. On the other hand, data-directed breadth-first forward
chaining is obtained if low level data assertions are placed above the assertions suggested by them.

### 2.2 Strategies for Heuristic Reasoning

A KBS operating in a realistically complex domain will use some form of inexact reasoning and
heuristics. The reasons for this are threefold:

- (i) The data and knowledge is unreliable.
- (ii) The data and knowledge is not static.
- (iii) The search space for solutions is potentially very large.

With ideal and/or simple KBSs, the knowledge and data do not lead to false, inexact, or tentative
conclusions. Once conclusions have been made by such a system, there is no need to modify or retract
facts in the light of new information (i.e. the system is displaying monotonic reasoning). In real-world
applications data can be noisy and error-prone due to extraneous measurements and missed observations.
Additionally, the knowledge captured in the system can be ill-specified in terms of its consistency and
correctness. A single line of reasoning, not supporting multiple arguments and multiple conclusions, is
therefore inadequate for many ill-conditioned, i.e. heuristic, tasks.

There are in general three main strategies for heuristic reasoning. Two of these are due to the classic
expert systems MYCIN (Shortliffe, 1976) which uses certainty factor theory and PROSPECTOR (Duda et
al., 1979) which uses Bayes' theory. The third strategy is to use fuzzy set theory due to Zadeh (1974).
ESs which employ heuristics defend their methodology only on the basis of the results they have
produced. The techniques have been criticised for being unnecessarily fabricated. For example,
MYCIN's own formalism for reasoning with uncertainty could have been replaced by the thoroughly
studied Bayes' theorem. Bayes' rule could be used to calculate the probability of a disease given some
evidence from the a priori probability of the disease and the conditional probabilities relating the
observations to the disease. The amounts of data being considered are so large, however, that conditional
independence of observations must often be assumed. The need to resort to an assumption of
independence is often seen to undermine the merits of the rigorous statistical model (Stefik et al., 1983). The PROSPECTOR system seeks a compromise by replacing the observations with subjective estimates of prior probabilities.

Zadeh’s approach to inexact reasoning is divergent from classical predicate logic and is called fuzzy logic. The theory provides characterisation of linguistic variables, e.g., high amplitude, mild polyphasicity, early latency etc., by a mapping of the numerical values of the variables in a fuzzy set into corresponding possibility values. For example the fuzzy proposition $X$ has high amplitude is characterised using the fuzzy set:

$$(X \in [0,10], 0.1), (X \in [10,100], 0.3), (X \in [100,\infty], 0.7)$$

The interpretation of the proposition $X$ has high amplitude is then taken to be $X$ may be less than 10 with a possibility 0.1 of having a high amplitude, between 10 and 100 with a possibility 0.3 of having a high amplitude, and so on. The possibility value has no direct relationship to a probability value. Conceptually, it represents the degree of certainty with which the value of an attribute is believed to be true. The possibility value is usually determined from a continuous function related to the (fuzzy) set of values for an attribute (variable).

There will be more said about fuzzy logic in the descriptions of the BAEP and EMG expert systems. First we describe briefly the heuristic methods used in MYCIN and PROSPECTOR.

2.2.1 Certainty Factor Calculations in MYCIN

When MYCIN makes a conclusion using its rules, a primitive fact will be added into its dynamic database together with a computed certainty factor for this fact. This certainty factor (CF) is computed from:

- (i) the combined certainty factors of the individual clauses in the rule premise,
- (ii) the certainty factor attachment of the rule, and possibly from the
- (iii) certainty factor of the original primitive fact if it existed already in the dynamic database.

The operation performed in (i) is simply the minimum CF of the premise clauses. This is multiplied by the CF attachment of the rule to give a certainty factor CR. CR is stored together with the primitive fact in the conclusion provided the conclusion does not already exist. If the conclusion already exists with a certainty factor of CI, then the computation in (iii) is done as follows:

$$CF = CI + CR (1 - CI) \quad \text{for } CR,CI > 0.$$  
$$CF = - (|CI| + |CR| (1 - |CI|)) \quad \text{for } CR,CI < 0.$$  
$$CF = \frac{CI + CR}{1 - \min(|CI|,|CR|)} \quad \text{for } CI,CR < 0 \text{ and } |CR|,|CI| \neq 1.$$  
$$CF = 1 \quad \text{with a combination of 1 and -1 for } CR,CI.$$  

Using these formulae, MYCIN is able to cope with non-monotonic judgemental reasoning. Shortliffe, provides a formalised description of the epistemology which is loosely based upon Bayes’ theorem. The variation in computed CF is shown in Fig. (1(a)), (Alty and Coombs, 1984).
Fig. (1(a)) Certainty factor interpolation in MYCIN.

Fig. (1(b)) Piecewise linear interpolation for dealing with uncertain evidence in PROSPECTOR.

Fig. (1(c)) The relationship between user-input certainty values and probability values used to calculate the odds allocated to hypothesis nodes.
2.2.2 Dealing with Uncertainty in PROSPECTOR

PROSPECTOR uses several hierarchical networks to represent mineral classification models. The nodes are connected by rules which use likelihood ratios for sufficiency (LS) and necessity (LN). LS and LN measure the degree to which a change in probability in one node will affect the probability of another at a higher level in its hierarchy. One way to visualise this arrangement is in terms of source nodes and target nodes. The source nodes contain facts used as evidence at lower levels in the PROSPECTOR model hierarchy, and the target nodes contain hypotheses at higher levels in this hierarchy. The target nodes are, in turn, the source nodes for higher level nodes, and so on. The top level of the hierarchy represents the goal of the model. This interpretation therefore reduces the network to a production rule representation having probabilistic attachments through the rule strength formalism; a vague similarity with a production rule-based system is evident.

The propagation of probability values in the model is driven by Bayes' theorem relating the hypotheses H to the evidence E:

\[ P(H|E) = \frac{P(E|H) \cdot P(H)}{P(E)} \]  

where \( P(H|E) \) is the conditional probability of \( H \) being true given \( E \), and \( P(E|H) \) is the conditional probability of \( E \) existing given \( H \). \( P(H) \) and \( P(E) \) are the prior probabilities of \( H \) and \( E \) respectively; these being estimated by the expert during the formulation of a PROSPECTOR model. Given that \( P(\neg X) = P(-X) = 1 - P(X) \), it can be shown that:

\[ P(-H|E) = \frac{P(E|-H)}{P(E)} \]  

Dividing Eq.(1) and Eq.(2) gives:

\[ \frac{P(H|E)}{P(-H|E)} = \frac{P(E|H)}{P(E|-H)} \cdot \frac{P(H)}{P(-H)} \]

therefore, if odds \( O(X) = P(X)/(1 - P(X)) \) then:

\[ O(H|E) = \frac{P(E|H)}{P(E|-H)} \cdot O(H) \]  

or, this equation may be rewritten as:

\[ O(H|E) = LS \cdot O(H) \]

which is the odds version of Bayes' theorem and relates, through the likelihood ratio LS, how the odds of \( H \) change with an observed true \( E \). Similarly:

\[ O(H|-E) = LN \cdot O(H) \]

informs us how to calculate the new odds of \( H \) given that \( E \) is definately untrue using the likelihood ratio LN.

LS and LN therefore provide a means of changing the prior odds of \( H \) if \( E \) is true and \( E \) is untrue respectively. One or the other is used as the rule strength depending upon whether \( E \) is true or untrue. They are related by the equation:

\[ LN = \frac{(1 - LS \cdot P(E|-H))}{(1 - P(E|-H))} \]  

\[ Eq.(4) \]
and generally \( 1 \leq LS \leq \infty \) and \( 0 \leq LN \leq 1 \) so that, for example, statements like: *if there is fire then there is smoke* can be made with a reasonable amount of certainty. A problem does exist however, since one may want to state that the presence of \( E \) will increase the odds on \( H \), but the absence of \( E \) will have no effect, i.e. in this case \( LS > 1 \), and \( LN = 1 \) which is inconsistent with Eq.(4) and probability theory. PROSPECTOR, nevertheless, has methods of dealing with this inconsistency.

The decision to use either \( LS \) or \( LN \) depends on whether or not \( E \) or \( -E \) are known with certainty. This is not usually the case, and in a perfect world it would be dealt with by a linear interpolation (Alty and Coombs, 1984). If \( E \) is known to be true with evidence \( E' \), e.g. \( P(E|E') \), then:

\[
P(H|E') = P(E|E') \cdot P(H|E) + (1 - P(E|E')) \cdot P(H|-E)
\]

One problem with this linear interpolation approach, is that when the network is set up, all nodes are assigned prior odds. Since \( LN \) and \( LS \) relate the prior odds across the network, an expert would have great difficulty in setting up a completely consistent network. The model building experts usually give the prior odds of nodes and the \( LN, LS \) values in a subjective manner. Thus the network will usually be mathematically inconsistent. If \( E' \) is the evidence that causes the user to suspect the presence of \( E \), then the probability of \( H \) will be altered to \( P(H|E') \). This will be between \( P(H|-E) \) and \( P(H|E) \). If \( P(H|E') \) has the value 0 then \( P(H|E') \) should be \( P(H|-E) \). When \( P(E|E') \) has the value 1, \( P(H|E') \) should have the value \( P(H|E) \).

If, however, we know nothing about \( E \) (i.e. \( P(E|E') = P(E) \)) then the prior odds on \( H \) should not change. Thus \( P(H|E') = P(H) \). These three points give us the relationship between \( P(H|E') \) and \( P(E|E') \) as shown in Fig.(1(b)).

This technique in PROSPECTOR overcomes the problem of inconsistent \( LN, LS \) and prior odds assigned to the network by the expert, thereby eliminating erroneous propagation of probabilities. It yields the relationships below for the piecewise approximations in Fig.(1(b)):

\[
P(H|E') = P(H|-E) + \frac{(P(H) - P(H|-E))}{P(E)} \cdot P(E|E'), \quad \text{for } 0 \leq P(E|E') \leq P(E), \text{ and}
\]

\[
P(H|E') = P(H) + \left( \frac{P(H|E) - P(H)}{1 - P(E)} \right) \cdot (P(E|E') - P(E)), \quad \text{for } P(E) \leq P(E|E') \leq 1.
\]

The same piecewise approximation technique is used to map user input probability values to the prior odds allocated to the spaces that prompt for that user input. The user supplies a certainty factor \( C(E|E') \) between 5 (the queried value is definately true) and -5 (definately not true). A value of 0 for \( C(E|E') \) has no effect on the prior probability, and the extreme values force the probability to 1 or 0.

The graph of \( C(E|E') \) against the prior probability \( P(E) \) is shown in Fig.(1(c)). The piecewise approximation relationships are:

\[
P(E|E') = P(E) + \left[ \frac{C(E|E')}{5} \right] \cdot (1 - P(E)), \quad \text{for } C(E|E') > 0, \text{ and}
\]

\[
P(E|E') = P(E) + \left[ \frac{C(E|E')}{5} \right] \cdot P(E), \quad \text{for } C(E|E') \leq 0.
\]

Suppose the user supplied the value of 3 for the certainty of a piece of evidence \( E \) which had a prior probability \( P(E) = 0.6 \) in the PROSPECTOR network. The adjustment made to the prior probability would then be \( 0.6 + (3/5)(0.4) = 0.44 \).

One last point to consider is the logical combinations of probability values between the nodes in the PROSPECTOR model. Combination with the logical operators AND, OR, and NOT is effected using Fuzzy set theory (Zadeh, 1974). For AND, the minimum probability is taken. For OR, the maximum probability is taken, and NOT simply negates the probability. A similar scheme is used in the MYCIN model of uncertainty reasoning.
2.2.3 Fuzzy Certainty Factor Calculations in EPAXIS and DEMGES

EPAXIS is an acronym of EP Analysis and eXpert Interpretation System (Sehmi, 1988a). It is a suite of programs used to automatically score the auditory brainstem evoked potential and includes the set of numerical Event Analysis programs. EPAXIS uses fuzzy certainty factors in its uncertainty mechanism, mainly because the fuzzy sets used can be specified easily from the normal values of component latency variability quoted in the literature. The use of two terms (i.e. the mean and standard deviation), permits the specification of errors in latency measurement to be invariant for many different types of evoked potentials and hence allowing EPAXIS to be extended into other EP domains.

The rules that EPAXIS contains are modelled on the judgemental processes that an expert uses for BAEP scoring. The data provided by event analysis are examined by EPAXIS rules in the early stages of a goal-directed reasoning process. Candidate choices for features are given fuzzy values which are propagated through the search space towards the final goal of finding waves I-V. Hence, the quantitative analysis results are easily assigned qualitative descriptions for the system to reason with. The method by which fuzzy values are assigned to the data relies on the definition of a fuzzy model for the normal brainstem potential. The model is described later. It is comprised of two parts, namely, the procedural and the declarative model components.

DEMGES, a Decomposition of EMG Expert System, is designed to decompose an EMG signal into its constituent MUAP trains at contraction levels where moderate superpositions of MUAPs occur. DEMGES performs an intelligent decomposition of the IPEMG into its individual MUAP trains at force levels up to 30% maximum voluntary contraction. In order to do this classification of both non-overlapping and superimposed MUAPs in the signal is required and the scheme used for uncertain reasoning is similar to that employed in EPAXIS. The difference lies in the way the fuzzy model of the underlying EMG generation process is constructed and used. The numerical algorithms in DEMGES provide the initial data required to construct the underlying EMG generation process and hence the subsequent derivation of the fuzzy model.

The details of the fuzzy models for both EPAXIS and DEMGES will be given in the discussion of these systems.

3. The BAEP Expert System (EPAXIS)

In this section a knowledge-based expert system is described which interprets symbolic evoked potential data provided by a non-linear peak detection algorithm (Event Analysis). The result is an assignment of characteristic labels to the averaged evoked potential. The system, written in Prolog, comprises some 50 rules that are driven by an interpreter that incorporates uncertain reasoning based on fuzzy set theory. A fuzzy model of the evoked potential is used which contains both procedural and declarative knowledge. The declarative part contains a description of the temporal relationships between the significant evoked potential components. The procedural part interacts with the declarative part through attachments that activate demon procedures which compute values for the evoked potential attributes and their fuzzy certainty factors.

Event analysis generates a discrete histogram of all events found in an ensemble of single-responses that comprise the average BAEP response. Fig.(2) shows an averaged BAEP response with the corresponding discrete and smoothed event histogram (event bins). The peaks in the smoothed event bin clearly delimitate islands of activity occurring in the averaged response. Together with this event bin information it is possible to find and label the major components in the averaged BAEP response, whether or not they can be observed as true turning points or as points of inflection in the averaged response itself. When the major BAEP components have been found by the expert system, their latency information is used in conjunction with information regarding the occurrence of events in the original single-response data to obtain a set of new averages. These averages are created from carefully selected sub-sets of the original single-responses. The set of new averages include traces which show enhancements to the individual BAEP components which were found by the expert system. In addition there are traces which are computed to emphasise some predefined relationships that are known to exist between components in a BAEP (e.g. the relationship between wave components I, III and V). This technique yields enhanced
Fig. (2) Averaged BAEP response with corresponding discrete and smoothed event bins. Smoothed event-bin peaks show those latencies at which BAEP components may exist.

Fig. (3) A mapping of event bin peaks onto the fuzz function provides a measure of reliability for these peaks and, in turn, for the corresponding averaged BAEP peaks if they exist.
averages of the BAEP by analysing only 64 single responses at 60dB auditory stimulus intensity. Latency variability estimates of the components can be made to within ± 2 sampling points i.e. ± 80µs at 25kHz sampling rate and signal-to-noise ratio ≥ -10dB (Sehmi, 1988b).

To enable the expert system to find the correct BAEP components data from the event binning process is initially written to files in the form of Prolog-readable terms. The expert system picks up these terms for subsequent interpretation. They have the following general format:

data(PeakType, NumberOfPeaks, ListOfPeaks).
ListOfPeaks = [Pos1/Amp1, ..., PosN/AmpN].
PeakType = bin_pks | grand_average_pks.

3.1 A Fuzzy Model Description for BAEP Interpretation

By examining the terms containing the event bin histogram data it is possible to get first estimates of where BAEP components exist in the averaged response. Several peaks in the event bin can cluster together in the immediate vicinity of one BAEP component and the resolution of which one of these is the most probable representative of the true BAEP component poses a small problem. This can be complicated even further by the anomaly that a distinct feature might not even exist in the averaged response itself. The real feature may have been smeared out by the averaging process (due to the inherent variability associated with the BAEP components in the single-responses) or it may be present as a point of inflection. The clustering of event bin peaks could also be due to noise contamination that has not been completely removed with the data reduction method. It is also plausible to suggest that multiple peaks in the event bin (especially in and around the later BAEP components) are due to the activation contralateral sub-cortical generator sites reflecting their activity in the recorded ipsilateral channel. These problems have led to the specification of a composite fuzzy model description of the BAEP.

3.1.1 The Fuzzy Procedural BAEP Model (Database)

The fundamental primitive for information modelling is propositional statements of the form: an attribute of an object has a particular value. This is represented in the Prolog language as the symbolic structure:

Object Attribute Value.

We may express that a wave component of the BAEP occurs at position X by writing:

Wave position is X.

However, when Wave does not occur exactly at X then a degree of imprecision is introduced, where X does not exactly reduce to one element in the domain Uwave (universe of discourse) of the variable Wave. X is then the set of mutually exclusive possible values for Wave. In the imprecise proposition above, the set X may not have clear boundaries. Then X is what Zadeh (1974) has called a fuzzy set and Wave position is X is said to be a fuzzy proposition. A fuzzy set X say, is described by means of a membership function µx. This is a function mapping from the domain Uwave to the interval [0,1]. A value of 1.0 represents full membership and a value of 0 represents non-membership. Intermediate values of µx for Uwave represent partial membership.

The fuzzy set (µx) of values which the results of event analysis (X') can take for a wave component (Wave) in the domain of BAEP waves (Uwave), is given uniquely by the fuzzy membership function (µx). The membership function for the domain Uwave is shown in Fig.(3). This is termed the fuzz function and enables assignments of reliability or fuzz to the results of the event analysis algorithm and the peaks in the averaged BAEP response.

Refering to Fig.(3), peaks in the bin segment shown, have their fuzz computed by a simple interpolation through a mapping of their times of occurrence onto the fuzz function. For example, the bin peak at 'B' maps to a fuzz of 1.0 indicating full membership of X in Uwave and 'A' maps to a fuzz of 0.8 indicating partial membership of X in Uwave.
Fig.(4) A fuzzy procedural model for Brainstem Auditory Evoked Potentials.

Fig.(5) Linear variation of fuzzy reliability factor (FRF) with rule certainty factor (Cf).
Fig. (4) illustrates the complete fuzzy procedural model for the BAEP. The fuzz functions are located along the time axis at the normal mean values (initially) for each component wave of interest. Prolog descriptions for each wave are constructed via the execution of the declarative model (explained later) when required. The generic Prolog structures for a fuzzy function (or, as we call it, fuzzy latency window) are:

\[
\text{fuzzwindow(WaveNumber, Anchor, } [P, Q, R, S]) \]
\[
\text{modifs(WaveNumber, } [a, b, c, d]) \]
\[
\text{current_shift(WaveNumber, Shift)}.
\]

where \([P, Q, R, S]\) are defined in terms of the modifiers \([a, b, c, d]\) in the \(\text{modifs}/2\) predicate. The modifiers are set to constant values, but conceptually they can be continuous functions of time that modulate their respective fuzz function regions. The Prolog predicate \(\text{current_shift}/2\), is used to relocate the anchor point for the fuzzy function along the time axis (see Fig. (4)).

### 3.1.2 The Fuzzy Declarative BAEP Model (Knowledge Base)

We have seen how the results of the event analysis algorithm can be assigned reliability measures. To reason effectively with these tagged items of data requires the declarative model and the inference engine (rule interpreter) to be compatible at a higher level.

This model attempts to capture the expert decision making processes used to interpret (label) a BAEP. The fuzzy procedural model described above makes it possible to formulate factual propositions of the form:

Object Attribute FuzzyValue.
FuzzyValue = Value + Fuzz.

Furthermore we can formulate the consequence of fuzzy propositions by using rules or productions:

if: Object Attribute FuzzyValue
then: ObjectX AttributeX ValueX.

Which reads: the value \(\text{ValueX}\) of object \(\text{ObjectX}\) is asserted with the fuzzyness \(\text{Fuzz}\) (contained in the structure \(\text{FuzzyValue}\)) of object \(\text{Object}\).

The certainty with which a proposition holds is expressed with a propositional attachment called the certainty factor, \(\text{cf}\). Therefore we can write:

if: ObjectX AttributeX FuzzyValueX cf CF
then: ObjectY AttributeY ValueY.

Which reads: the value \(\text{ValueY}\) of object \(\text{ObjectY}\) is asserted with a combination of the fuzzyness \(\text{FuzzX}\) of object \(\text{ObjectX}\) and the \(\text{cf}\) attachment \(\text{CF}\) : \([0.0, 1.0]\). This in effect allows the modeler to express the reliability or confidence with which a proposition is being made when the object value is completely true. If the object value is fuzzy, then this is reflected nevertheless through a combination of fuzzy and certainty values.

The production if contralateral recording is available then contra_wave_Y position is X, produces a piece of evidence that may be needed for reasoning whilst the antecedent is true, but the evidence is not terribly important if the antecedent is false. To prevent the assertion of the consequent with a low certainty value in the absence of a contralateral recording, another extension to our existing formalism is required. In this case we must assign a weighting to evidence for truth and a weighting to evidence for falsehood:

if: ObjectX AttributeX FuzzyValueX cf CF wt (WtT,WtF)
then: ObjectY AttributeY ValueY.
Because of these clause weights, the combined fuzzy value for object ObjectX must be calculated in two stages:

Stage 1: \[ Fuzz = FuzzX \cdot CF \]

Introducing the clause weights \((WtT, WtF)\) we obtain a total reliability for the antecedent proposition in the production rule. This is termed the fuzzy reliability factor (FRF):

\[ FRF = \frac{WtF + Fuzz(WtT - WtF)}{\max(WtT, WtF)} \]

Which reads: the value ValueY of object ObjectY is asserted with the fuzzyness FRF of object ObjectX.

Fig.(5) illustrates the variation of the clause weight (FRF) with the certainty factor attachment (or combined fuzzy value) of the rule proposition. The contribution of truth and falsehood to the declarative interpretation of an antecedent proposition (and how much this contributes to the assertion of consequent propositions), is determined by the truth and falsehood weights. Adjustments of these weights is equivalent to an adjustment of the slope of the line in Fig.(5). The steeper the positive slope, the higher is the contribution of truth of antecedents in the assertion of consequents, and the less falsehood detracts. Negative slopes have the same effect as negation of the antecedent propositions. Use of weights that produce negative slopes is not recommended as it obscures the declarative content of the rules.

Rules containing conjunctions of antecedents get their individual FRFs combined before the assertion of a consequent using the following relationships:

\[
\begin{align*}
\text{ClauseWtA} &= WtFA + FuzzA(WtTA - WtFA) \\
\text{ClauseWtB} &= WtFB + FuzzB(WtTB - WtFB)
\end{align*}
\]

\[
\text{etc.}
\]

\[ FRF = \frac{\text{ClauseWtA} + \text{ClauseWtB} + ... + ...}{\max(WtTA, WtFA) + \max(WtTB, WtFB) + ... + ...} \]

where a clause weight ClauseWtX is the individual FRF of a single antecedent X in the conjunction. If the consequent also has a certainty factor attachment, then the FRF calculated using the above relationships is combined with it as in stage 1 above (i.e. the overall fuzzy value = FRF \cdot CF of the consequent).

The above ideas are employed in a structured declarative model (knowledge base of rules) which has a syntax suitable for creating expressive propositions.

3.1.3 Knowledge Base Structure

The rules contained in the knowledge base are grouped into:

Control (meta) rules

These are rules that direct the search through the state-space when driven by the inference engine or rule interpreter. The task requires some direction as to which BAEP waves to look for in the absence of others. For example:

```
rule19 :: if
    channel = ipsi & wave_I = found & wave_II = found &
    wave_III = found & wave_IV = not_found &
    wave_V = found & wave_V_complexity = yes
then
    all_peaks = found & complex_on_wave_V = yes.
```
Descriptive rules

These are rules which produce qualitative descriptions of the BAEP. They activate (and are in fact higher level abstractions of) the characterising rules described below. Descriptive rules are useful for two reasons. First, they provide clear declarative semantics of what is being performed in the interpretation task which is useful in the debugging phase (and most notably for producing understandable explanations of the reasoning paths taken). Second, the abstraction allows for increased generality and therefore re-use of the same rules in other EP domains. An example of a descriptive rule is:

```
rule02 :: if
  Wave list_of_pks_is ListOfPks+(bin_pks) &&
  Wave best_pk_is Pos/Fuzz+(ListOfPks)
then
  Wave position_is Pos cf Fuzz.
```

Characterising rules

The knowledge base can be viewed as an AND/OR graph with its leaves being the conjunction of the antecedents in these characterising rules. Specific knowledge about BAEPs is handled entirely by these rules. They provide the interface with the BAEP data through procedural mappings that activate demons. These rules return appropriate Prolog data structures which are examined and the results are propagated upwards in the state-space from this level. Example characterising rules are:

```
rule10 :: if
  Wave mean_is Mean &&
  Wave sd_is Sd
then
  Wave stats_of_are (Mean, Sd).

rule04 :: if
  WaveX position_is PosWaveX &&
  WaveY is_expected_at PosWaveY+_Tol_+(WaveX) &&
  $(Temp is PosWaveX - PosWaveY) && $(abs(Temp, ExpectedInterval))
then
  WaveX to WaveY expected_interval_is ExpectedInterval.

rule05 :: if
  WaveX position_is PosWaveX &&
  WaveY expected_at PosAndTolWaveY+(WaveX,PosWaveX)
then
  WaveY is_expected_at PosAndTolWaveY+(WaveX).

rule35 :: if
  channel = ipsi && wave_I position_is PosWave_I &&
  ( wave_I is_expected_at EPos_I+Tol_I+wave_III) or
  wave_I is_expected_at EPos_I+Tol_I+wave_V ) &&
  $(TempDiff is PosWave_I - EPos_I) &&
  $(abs(TempDiff, Diff)) && $(Diff =< Tol_I)
then
  pos_wave_I_at = PosWave_I.
```

The corresponding demon procedure mappings are performed through a predicate defined as external/2:
Fig. (6) Enhanced averages produced by the intelligent selection of single BAEP responses. The vertical lines through the traces correspond to the mean latencies of the peaks marked (*) in Fig. (2).
The next section will go on to describe very briefly the top level interpreter used in this system.

3.2 The EPAXIS Interpreter

This interpreter shell is backward chaining and provides uncertain inference and explanation capabilities for the declarative model described in the previous section. It also provides the interface with the procedural model through invocation of the user-defined demon-procedures. The interpreter executes the declarative model (i.e. knowledge base) in much the same way as Prolog executes the interpreter itself. Hence, it is possible to pass goals to Prolog for execution. This is necessary for mathematical constructs and interfacing to other languages. An important specification for this implementation has been separation of all EPAXIS modules. In this respect the same interpreter can be used to execute knowledge bases defined for interpreting different EPs.

The structure used in the shell derives from the work of Niblett (1984). The implementation of uncertain reasoning is a variant of that described by Lebailly et al. (1987). The scheme below shows the basic structure of the EPAXIS interpreter:

```
% Top call
solve(Goal) :- solve(Goal, Fuzz, []).
% Is goal known
solve(Goal, Fuzz, _) :- known(Goal cf Fuzz), !.
% Is goal solvable using a procedural call
solve(Goal, Fuzz, _) :- external(Goal,Demon), !, execute_demon(Demon, Fuzz).
% Is goal solvable using a math call
solve(Goal, Fuzz, _) :- call(Goal), !, certain(Fuzz).
% Is goal solvable using a rule
solve(Goal, Fuzz, Proof) :-
    getrule(Rule :: if Conds then Goal),
    satisfy(Conds, CondsFuzz, [Goal+Rule|Proof]),
    conclude(Goal,CondsFuzz, Fuzz).
% Ask user for solution
solve(Goal, Fuzz, _) :- askable(Goal), !, certain(Fuzz).
```

`satisfy/3` attempts to solve the antecedent propositions by recursively invoking `solve/3` with each proposition in turn. A successful goal will cause `satisfy/3` to calculate its fuzzy value (FRF) and eventually a combined fuzzy value (CondsFuzz) for all propositions. `conclude/3` will then assert the conclusion with the fuzzy value of the antecedents combined with the certainty factor of the rule if it exists.

In the case when goals are already known (i.e. they have been proved already) and the antecedent proposition has a certainty factor attachment, a simple product of fuzzy values is performed before the calculation of the FRF. A similar multiplication process is performed if the assertion of a consequent has a precedent. This latter process allows the accumulation of evidence for some items to dynamically strengthen or weaken evidence for others.

The resulting enhanced averages obtained from a single channel BAEP recording is shown in Fig.(6). It is intended to extend both event analysis and EPAXIS into multi-channel EP recording regimes. This will help to enhance the understanding of neuronal communication mechanisms in the brain, by analysing data containing temporal information which has been obtained spatially over the scalp.
Fig.(7) Functional overview of the DEMGES expert system. Numerical analysis provides general MUAP information for use in decomposing overlapped MUAPs.

Fig.(8) The internal structure of the DEMGES expert system.
The effectiveness of the above fuzzy descriptions of the data and the use of a fuzzy reasoning mechanism will only be determined through an extensive validation study. This work will continue in the future and encompass other EP domains and eventually it is hoped it will prove more generally useful in signal processing for pattern recognition, decision making and control.

4. The EMG Expert System (DEMGES)

DEMGES is a rule-based expert system. Decomposition of the myoelectric signal is performed using symbolic information provided by a numerical MUAP recognition procedure (see Fig.(7)). The system is written in Prolog and consists of some 30 rules in the knowledge base that are driven by an interpreter that incorporates uncertain reasoning based on fuzzy set theory. Like EPAXIS, there is a procedural and declarative knowledge representation of the problem domain.

The rules that DEMGES contains are modelled on the judgemental processes that an expert uses for decomposing superimposed waveforms. The MUAP candidates in a combination, initially determined by the procedural analysis, are given fuzzy values which are propagated through the search space towards the final goal of finding the certainty with which various MUAP combinations form a superimposed waveform. A fuzzy model describing the myoelectric signal is used to assign fuzzy values to the MUAP combinations. The fuzzy model contains both procedural and declarative knowledge.

4.1 The Fuzzy Procedural Model (Data Base)

MUs do not fire at exactly regular intervals under constant force level conditions. Therefore it is not certain which MUAPs form a superimposed waveform. MUAP candidates are given fuzzy values related to the possibility of a MUAP occurring at the position of a superimposed waveform. The fuzzy value is calculated using the fuzzy membership function shown in (a) of Fig.(8). The fuzzy membership function represents the firing period distribution of a MU. In reality the distribution is slightly skewed.

The fuzzy value of a MUAP candidate is calculated by mapping the smallest firing period (SFP) between the nearest neighbouring MUAP in the MUAP train and the position of the superimposed waveform onto the fuzzy membership function (see (b) in Fig.(8)). The width of the fuzzy function varies for each MUAP train in the myoelectric signal, depending on the mean and standard deviation of the firing periods in the MU under consideration.

4.2 The Fuzzy Declarative Model (Knowledge Base)

This model attempts to capture the expert decision making process used to decompose superimposed waveforms. DEMGES uses fuzzy rules in the same manner as explained in EPAXIS to describe the consequence of fuzzy propositions. DEMGES rules do however contain weighting factors.

The modeller is also allowed to express the reliability or confidence in a rule being true through a rule attachment called a certainty factor cf.

if : Object Attribute FuzzyValue
then : ObjectX AttributeX ValueX cf CF.

In this case, the value ValueX of object ObjectX is asserted with a combination of the fuzzyness Fuzz (in FuzzyValue) of object Object and the cf attachment CF. The fuzzyness FuzzX for ValueX is then:

\[ FuzzX = \min(Fuzz, CF) \]

The premise of a rule can contain both conjunctions and disjunctions of propositional clauses. The combined fuzzy value of a conjunction or disjunction of clauses is determined using fuzzy set theory. In a conjunction the minimum fuzzy value is taken from the computed fuzzy values in the set of clauses in the premise. In a disjunction the maximum fuzzy value is taken.

The example below shows a rule containing a conjunction of two propositional clauses and the conclusion of the rule being given a confidence or certainty factor.
Fig.(9) Pictorial summary of the results from DEMGES.
Some rules in the knowledge base (e.g. rule 19 above) cater for problems that arise when the SFP is much greater than the mean firing period of a MU (due to unclassified MUAPs) as shown in (b) of Fig.(8). This is done by repeating the fuzzy membership function at multiples of the mean firing period. These rules are given certainty factors (or confidence values) that reduce in value as the SFP increases with respect to the mean firing period of a MU. Graph (c) of Fig.(8) shows the effect on confidence in the rules at increasing multiples of the mean firing period of a MU. This behaviour is captured in DEMGES by using additional rules similar to rule 19 above, each having a different cf value. The ordering of the rules in the knowledge base and Prolog’s in-built backtracking control mechanism results in the gradual decay of confidence values being produced. Other rules determine the effect a MUAP’s position has on the outcome of the result. These rules calculate the overall fuzzy value of each candidate MUAP combination (Z) in a superimposed waveform. The formula used to find the overall fuzzy value is:

\[ F(Z) = F(X) \cdot NOT(F(Y)) \]

where \( F(Z) \) is the overall fuzzy value of a MUAP combination, \( F(X) \) is the combined fuzzy value of the intersecting set of individual MUAPs in a combination and \( F(Y) \) is the combined fuzzy value of the exclusive set of individual MUAPs not in a combination.

The interpreter shell used to perform the decomposition of superimposed MUAPs in DEMGES is based on the shell used in EPAXIS. Minor changes to a module where fuzzy values are calculated and propagated in the search state-space.

### 4.3 The User Interface

DEMGES displays information on how the myoelectric signal under analysis has been classified and the MUAPs from the different MUs that have been extracted. The top level of Fig.(9) shows a simulated myoelectric signal containing four labelled motor unit trains. One can query the findings that superimposed waveforms contain a specific combination of MUAPs. In the highlighted superimposed waveform, the suggestion that MUAPs two and three comprise the superimposed combination is queried by selecting the waveform in the myoelectric signal using a mouse pointing device. The mid-level of Fig.(9) shows an expanded section of the queried superimposed waveform. Statistics of the suggested constituent MUAPs are also given.

The lower-level of Fig.(9) shows a pop-up window that displays the fuzzy certainty values of the final result. All other possible combinations of MUAPs that could have formed the selected superimposed waveform are also given together with their fuzzy certainty values. The user is then given the option to study how the conclusions were formed. The how explanation displays the trace of reasoning taken by the expert system by interpreting the proof-tree built up in reaching that conclusion. The user is also able to study any rule invocations to seek a more specific explanation to a query.

### 5. The EEG Expert System (Jansen and Dawant, 1989)

Many attempts have been made to automate the quantification and interpretation of the electroencephalograph (EEG). Initially based upon numerical procedures operating on segments of the EEG signal followed by pattern classification, they have been largely unsuccessful due to their omission of contextual information. This information relates to the important spatio-temporal relationships that exist between features in the 20+ channels of EEG data that can be recorded in any one measurement. The
expert system described here due to Jansen and Dawant (1989) is a feasibility study to determine the effectiveness of using context information to perform automatic sleep EEG analysis. Their approach employs object-oriented principles where expected features in the EEG waveform and sleep stages are represented as objects or frames. This form of knowledge representation has been described previously and is particularly suited to capturing such stereotypical situations. The control scheme associated with such a representation is an advantage since the system can behave opportunistically and extract numerical indices from the data only when required and only in the context as determined by the current line of reasoning. Therefore this system can be viewed as having a deeper knowledge of the underlying signals, their inter- and intra-relationships and hence it can plan an interpretation more effectively than both EPAXIS and DEMGES described earlier.

This expert system was designed specifically to detect sigma spindles (bursts of quasi-sinusoidal activity in the 12 to 16Hz range) and K complexes (bi- or triphasic slow waves with a duration of 0.5 - 1 s) in the sleep EEG.

5.1 The System

The overall system consists of five main components: a blackboard; a collection of object descriptions; a set of specialists; a scheduler and an object detection module.

5.1.1 The Blackboard

The blackboard is a central data structure that acts as a message passing mechanism between different parts of the system. It is also where control information and the state of the analysis situation are reported. The control information consists of a list of active, performed and requested operations. A requested operation triggers a series of actions to be performed on a particular type of object which is supervised by the scheduler.

5.1.2 The Object Description Units

The object description units are representations of the event situations the system has to detect. These representations are described in terms of frames. Each frame has a series of necessary and optional slots used by the detection module. The necessary slots are those needed by the system to successfully perform its task. The optional slots are used to completely describe each individual event. The object description for a sleep_spindle and a spat_sleep_spindle are shown in Table (1):

<table>
<thead>
<tr>
<th>sleep_spindle</th>
<th>spat_sleep_spindle</th>
</tr>
</thead>
<tbody>
<tr>
<td>TYPE</td>
<td>TYPE</td>
</tr>
<tr>
<td>Frequency_burst</td>
<td>Frequency_burst</td>
</tr>
<tr>
<td>NAME</td>
<td>NAME</td>
</tr>
<tr>
<td>Sleep_spindle</td>
<td>Spat_sleep_spindle</td>
</tr>
<tr>
<td>PRIMARY_LOCATION</td>
<td>PRIMARY_LOCATION</td>
</tr>
<tr>
<td>Central_right</td>
<td>No value</td>
</tr>
<tr>
<td>Central_left</td>
<td></td>
</tr>
<tr>
<td>NECESSARY</td>
<td>NECESSARY</td>
</tr>
<tr>
<td>Amplitude_frequency</td>
<td>Amplitude_frequency</td>
</tr>
<tr>
<td>SUPPORTIVE</td>
<td>SUPPORTIVE</td>
</tr>
<tr>
<td>Spatial</td>
<td>Spatial</td>
</tr>
<tr>
<td>SPATIAL</td>
<td>SPATIAL</td>
</tr>
<tr>
<td>Spatial_spindle</td>
<td></td>
</tr>
</tbody>
</table>

Table (1) Object description units for sleep_spindle and spat_sleep_spindle.

The TYPE, NAME, PRIMARY_LOCATION, NECESSARY and SUPPORTIVE are necessary slots, whereas SPATIAL is an optional slot. The value of TYPE describes the class of the event or activity being sought in the signal analysis and NAME describes the clinical EEG term for the event. The value of PRIMARY_LOCATION indicates probable location of the event during multi-channel analysis. The value of the NECESSARY slot describes the essential parameters that need to be matched between an object description and an event of the object's TYPE. The values of the SUPPORTIVE slot are also matching descriptors but are only used if a
definite decision cannot be reached based on the values of the NECESSARY slot alone. The values of NECESSARY and SUPPORTIVE refer to a series of specialists that can return a value for the desired characteristics. Optional slots can be used when arguments are required by the specialists. SPATIAL is an optional slot and specifies the name of a class of rules that is to be used by the spatial specialist.

5.1.3 The Specialists

Specialists are units that range from a simple numerical routine to a more knowledge intensive subsystem. The specialists perform operations on objects and can detect specific events or compute certain characteristics for those events already detected. They react to requests placed on the blackboard and return their results to the blackboard. A specialist contains triggering knowledge to decide when to contribute to a solution and computational knowledge on how to do it. Specialists can either act as detectors or evaluators. Detection specialists look at the data and look for a certain type of event within a given range of parameters. If such an event is found, a new unit is created by the specialist and put on the blackboard. Evaluation specialists act on units that already exist and provide a rating of the quality of the match between expected and computed values of certain attributes (the ratings for good quality are yes, no and doubtful). Because of the independent structure of the specialists, they can be modified, removed or new ones added without affecting the rest of the system.

5.1.4 The Scheduler

The scheduler is mainly concerned with the management of the list of requests placed on the blackboard. The scheduler looks for specialists that can fulfill the requests, resolve conflicts and interrupt and reactivate tasks.

5.1.5 The Object Detection Module

The object detection module detects events in the EEG data using frame matching procedures. The module is a set of rules that requests the calculation of specific characteristics. The request triggers the appropriate specialist to scan the data to determine if an object given by the TYPE slot can be detected.

5.2 Spindle and K Complex Detection Knowledge Bases

The knowledge base for sleep spindle detection consists of object description units, sleep_spindle and spat_sleep_spindle and specialists, frequency_burst, amplitude_frequency and spatial. The frame for a sleep_spindle (table 1) shows that a spindle is a burst of frequency activity, detected by the specialist frequency_burst. This activity occurs mainly in the central channels and it must meet amplitude and duration criteria specified by the amplitude_frequency specialist. If this specialist cannot ascertain the existence of such activity then a spatial analysis is performed by invoking the spatial specialist which in turn triggers a set of spatial_spindle rules that capture the spatial relationships that a candidate sleep spindle needs to fulfill before it can be upgraded to a genuine sleep spindle. The spatial_spindle rules can initiate a search for spindles in the frontal channel and in order to avoid cyclic deadlocks the spat_sleep_spindle frame is used whose PRIMARY_LOCATION value gets assigned by the the spatial_spindle rules themselves. The filtering performed by the frequency_burst specialist is performed by a filter specialist which has knowledge about what filtering is to be performed on the basis of the intended purpose of the filtering.

The knowledge base for k complex detection consists of two object description units, k_complex and sich_k_complex. The specialists are slow_wave, amplitude and refract which together find slow waves and apply amplitude and refraction criteria. Both spatial and temporal analysis can be performed to detect k complexes through the use of appropriate rule sets in situations where k complexes are rated doubtful.

The EEG expert system uses an opportunistic approach to EEG interpretation and therefore caters for both simple and complex situations. The system also contains a knowledge representation scheme that separates domain knowledge (about the EEG) and general signal analysis as represented by the specialists. Jansen and Dawant provide traces of the reasoning process taken in the interpretation of 3-channel sleep
EEG stage-2 data recorded from an 11-year, 2-month-old girl. The data contained both spindles and k complexes. Performance at this feasibility stage was encouraging and it was concluded that this architecture could become generally applicable in signal processing and interpretation.

6. Discussion

The descriptions of the various expert systems given above have covered production rule-based and frame-based signal analysis and interpretation. The two representation paradigms and their associated control aspects have also been described in some detail. We have seen that the frame-based approach can be mimicked in a rule-based system. Opportunistic behaviour with this form of representation is however limited by the difficulty in writing rules because of the need for including a large number of conditional propositions for guarding or screening purposes. In addition to this difficulty, focus of control must be effected by a strict ordering of rules (in DEMGES) and/or the use of meta-rules (in EPAXIS). Both of these difficulties reflect in problems we have encountered with knowledge base extensibility and maintenance. As a result, though we need to incorporate more complex behaviours by adding more rules, this is avoided.

The frame-based representation is a better structure for encapsulating knowledge about independent stereotypical events that one expects to observe in signals. The frames simply contain the attribute descriptions of the events and the associated procedural knowledge required to extract values from the data for them. Symbolic knowledge can be attached to frames as sets of production rules which become activated when contextual considerations need to be taken into account. The blackboard architecture (Nii, 1986a,b) used in the EEG expert system is an adequate platform to construct such a scenario since the frames can communicate with each other through the blackboard and their sequencing can be controlled by the scheduler. The frame-based approach achieves a greater separation of declarative and procedural knowledge than the production rule-based system and therefore knowledge-base extensibility and maintenance becomes easier. Thus incorporating more complex behaviours by adding more frames and associated rule-sets need not be avoided as was the case with a production rule-based system.

To bring KBSs into clinical use requires much more research to be done especially in the design of man-machine interfaces and tools for the nonexpert user. Knowledge acquisition must be made simpler and explanation facilities need to be enhanced and supplemented with user-friendly graphical interfaces. Also, more than one primary mode of signal analysis should be provided and preferably with some form of simulation of the data and/or of the patient system under study. In such an environment a clinician would be able to analyse both simulated and real data with a variety of methods and make objective assessments of an algorithm's ability to give useful information.

Including simulations in a KBS is an effective way of producing what-if question and answering mechanisms. The clinician can monitor the simulation responses and then plan the next line of questioning of the system. This demonstrates a deeper reasoning capability for the systems as a whole. The fact that the clinician is brought into the interaction to investigate possible effects of, say, treatment plans and adjustment of patient model parameters would make such systems easier to accept in the clinical environment. Fig.(10) shows a schematic diagram of a hybrid knowledge-based signal processing and simulation system as might be used in a clinical environment. This structure is generally applicable to other domains.

Realistically, the KBS in Fig.(10) would be called upon to manage several loosely coupled subtasks in the domain (e.g. some aspects of signal processing, interpretation of results, management of the consultation, invocation of patient-specific simulations and intelligent presentation of results to the user). In some cases the system would be required to incrementally construct a picture of the current status of the patient from available measurements and clinical observations of him. Incremental construction of a diagnosis or interpretation is important because partial evaluations can be considered without the restriction of insisting upon a final solution.
Blackboard system architectures offer a possible framework within which to build such automatic problem-solving systems. From a systems point of view, the modularity, dynamic control, efficiency and possibilities for concurrency offered by this architecture are good reasons why it would be preferred over the simple production rule-based system models. As a problem-solving framework, particularly in signal processing, blackboard systems offer the possibilities of integrating many types of knowledge, hierarchically structuring the sources of knowledge and the solution appearing on the blackboard and being able to build these solutions incrementally as and when information becomes available. The EEG expert system discussed above has demonstrated quite nicely that such systems are indeed worth considering for knowledge-based signal processing especially in medicine where data is often interpreted within a context which is constantly changing. Fig.(11) shows a typical blackboard system architecture which contains independent knowledge-sources (KS), a hierarchically organised blackboard and some scheduling control mechanisms. The KSs can be implemented through the frame-based approach and each one attributed to the task of detecting a specific event in a particular signal for example. Some KSs could be allocated to the data acquisition and low-level numerical processing, and others could manage the simulation processes and intelligent presentation of information to the user. In this system, the monitor receives data from the blackboard which can be used to intelligently focus the search for a solution to the current problem at hand. A prioritised agenda of competing hypotheses is maintained by the scheduler which will invoke the appropriate KSs in turn until the solution is found or the agenda becomes empty.

The availability of powerful low-cost digital signal processing (DSP) and graphics system processing (GSP) devices and equally powerful personal computers (IBM-PC 386) with large core memory (4 MB) now makes it possible to implement realistically complex knowledge-based systems for signal processing. Software development tools such as Microsoft Windows, C and Glockenspiel C++ under the DOS operating system, Quintus/LPA Prolog running under extended DOS mode and high-level compilers for the DSP and GSP devices assist in the development and prototyping of embedded systems with rapid acquisition, preprocessing and display of data. The author's are currently using the above tools and are developing a general hardware platform for distributed DSP/GSP processing to be hosted by an IBM-PC 386. The proposed system architecture is shown in Fig.(12) and it is intended to use the server side to run the blackboard system shown in Fig.(11) and the client side to run all intensive digital signal processing. Each channel of input can be managed by a knowledge source and the blackboard can be distributed between the server and client sides over the common DSP/PC RAM buffer area. As the various aspects of the hardware and software design get completed, the system should evolve into a powerful tool for real-time knowledge-based signal processing and simulation of multi-dimensional data.

7. References


Niblett T. (1984), Yapes - Yet another prolog expert system, Turing Institute research memorandum, TIRM-84-008, Turing Institute, Glasgow.


Fig. (11) The blackboard distributed knowledge-based software architecture.

Fig. (12) The distributed graphics and digital signal processing (GSP/DSP) hardware architecture to host simulation and real-time knowledge-based signal processing of multi-dimensional data.
Fig.(10) A hybrid environment for patient-specific simulations and knowledge-based diagnosis and signal interpretation.
Appendix 7

The main data flow and structure diagrams used in the software design of the new EMG decomposition method.
(1) Filtering of the EMG signal
(2) Normalising the processed signal
(3) Segmenting the normalised signal
(4) Classification of non-overlapping MUAPs
(5) Decomposition of superimposed waveforms

The top level data flow diagram of the software design.
The structure diagram shows the filtering stages of the analysis.

The structure diagram shows the normalisation stages of the analysis.
The structure diagram shows the segmentation stages of the analysis.

The structure diagram shows the main stages of the MUAP classification.
The structure diagram shows the classification of non-overlapping MUAPs in the analysis.

The structure diagram shows the decomposition of superimposed waveforms.