AUTOMATIC QUANTITATIVE ANALYSIS

OF NEEDLE RECORDED EMG SIGNALS

by

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ABSTRACT

A procedure for the recording and storing of EMG signals for the automatic extraction of individual motor unit rate coding and morphological information was developed. The extraction of the rate coding information is performed by the analysis of individual motor unit action potential trains (MUAPT'S), obtained by decomposing the composite EMG signal, recorded from a selective surface of a needle electrode. The morphological information is derived from the analysis of macro motor unit potentials (MUP'S). The macro MUP'S are the result of ensemble averaging the cannula recorded signal, using the individual MUAPT'S as sources of synchronizing triggers for the averaging process. A standard single fibre or macro EMG needle electrode can be used.

Signals recorded during isometric, constant or slow force varying contractions, up to 50% of the maximum voluntary contraction level, can be successfully analyzed. The number of motor units simultaneously studied, usually ranges from 3 to 5. The processing of the data, for each second of muscle contraction, can be performed by a PDP 11/34 computer in approximately one minute, with 95% accurate, rate coding information obtained. This speed and accuracy may increase the clinical use of rate coding information. The procedure also provides, individual motor unit rate coding and morphological information simultaneously, allowing correlation of motor unit sizes with firing rates and identification of macro MUP'S for high threshold motor units.

TO BARB, KARI, GREG and CLANCY

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CHAPTER 1

INTRODUCTION

It has been known for many years that muscle contraction is initiated and controlled by neural inputs. The basic contractile element of muscle force production is the motor unit. A motor unit is defined as an alpha motor neuron and all the muscle fibres innervated by its axon (Katz 1966). When the motor neuron of a motor unit fires an electrical impulse, all the muscle fibres of that motor unit contract, causing a muscle twitch. The twitches of many independently contracting motor units summate to create a smooth muscle contraction (Guyton 1977). In this way, the motor unit acts as the basic incremental element of force used by the nervous system for the control of muscle tension.

One way the nervous system changes the level of muscle contraction is to change the firing rates of the active motor units. This method of control is called rate coding. Controlling the number of motor units active is the other way the nervous system controls muscle contraction intensities. This control mechanism is called recruitment. These two mechanisms are the only ones used by the nervous system for the control of muscle contraction (De Luca 1979).

Motor unit morphology deals with the size, number and distribution of its component fibres. Muscles are composed of a varying number of motor units ranging from less than one dozen to several thousand. The identified size of a motor unit is determined by the amplitude of its twitch tension. Motor unit size is thus dependent on the number of fibres and the diameter of the fibres in the motor unit. The number of fibres in a motor unit ranges from several to several thousand. The circular area within a muscle in which fibres from a specific motor unit can be found varies usually from 3-10 mm in diameter (Buchthal et al 1959, Stalberg and Antoni 1980). This area is called the motor unit territory. Fibre distributions within motor unit territories are normally, random, uniformly distributed (De Luca 1979). The motor unit territories of many motor units overlap considerably (Bucthal et al 1958).

Contraction of muscle is accompanied by substantial electrical activity. The basis of this electrical activity are the muscle fibre action potentials (MFAP), which propagate outward from the innervation zone in both directions the length of the muscle fibre each time a muscle fibre contracts. The temporal pattern of this electrical activity is caused by the neural inputs to the muscle. The amount and spatial distribution of this electrical activity is determined by the number, size and distribution of the active muscle fibres. Therefore, the electrical activity associated with muscle contraction can be considered as an information source of both neural input and muscle morphology.

By the use of suitable electrodes and amplification, the electrical activity of muscles can be measured. This measured activity is called an electromyographic (EMG) signal. EMG signals then, can contain information about both the neural input, during contraction and the morphology of the muscle from which they were recorded.

Motor units active during a contraction and with fibres in the measurement volume of the recording electrode will contribute to the EMG signal. Due to the almost synchronous firing of all the fibres of the motor unit, their propagating electrical activities (their MFAP's) summate at the recording electrode to create the motor unit action potential (MUAP). Due to unique geometries of the fibres of each motor unit relative to the electrode, the recorded MUAP's will have unique shapes and sizes. Rate coding information can be extracted from the EMG for these motor units by analyzing the temporal spacings of the individual MUAP's in the EMG. Morphological information can be obtained by measuring features of the EMG that pertain to the spatial distribution of the electrical field created by the contracting motor units.

Rate coding and recruitment information are of interest to physiological researchers. They hold the key as to how the muscle contractions used for various different bodily functions are controlled. Clinically, this information may be very useful. Neural control changes, with different pathologies, may prove to be powerful diagnostic indicators. Presently however, this information is not clinically available, nor are its clinical parameters fully understood. Muscle morphological information, also of interest to physiological researchers, is the prime diagnostic tool presently used by clinical electromyographers. This information allows the clinician to estimate the number of motor units in a muscle, their size, distribution and fibre densities. These estimates, when compared to normative data, help determine the clinical state of the muscle in question.

The specific information in an EMG signal is a direct function of the type of electrodes used and the state of contraction of the muscle. To extract information about individual motor units, the EMG signals must be recorded with very selective electrodes which register the activity of only a few motor units at any one time. Selective electrodes and moderate levels of contraction will allow the components of each individual motor unit to be recognized in the composite EMG signal. This, in turn, will allow information pertaining to each individual motor unit to be obtained. If the EMG signal becomes too complex to determine the individual motor unit contributions, only parameters dealing with the whole electrode measurement area will be available. Individual motor unit control and morphological information will not be obtainable.

The work presented in this thesis was initiated in an effort to determine a signal collection and processing technique which can extract both individual motor unit rate coding and morphological information from an EMG signal as accurately and efficiently as possible. Consequently, this work will be dealing with selective needle electrode EMG recording techniques.

The nature of the composition of EMG signals is outlined at the beginning of Chapter 2. Present needle electrode EMG recording and analysis techniques and the information obtained are then reviewed. This chapter deals specifically with comparing different EMG signal compositions as a function of the type of recording electrode and contraction protocol used. It discusses the information that is presently extracted from the EMG signals recorded under the various protocols.

It was evident from this review that the extraction of motor unit specific neural control information is a tedious undertaking. This has limited the amount of this information available. Therefore, the emphasis of the signal recording and processing protocol developed here is on the extraction of this type of neural control information.

The remainder of Chapter 2 deals with the recording protocol adopted. The reasons it was chosen, its advantages, limitations and the information to be extracted is also reported.

Chapter 3 outlines the data collection-compression scheme that was used to efficiently digitize, collect and store the recorded signals. The logical need for data compression and the criteria used to effect it are stated. The software and hardware components of the data collection-compression are explained. The structure of the software and hardware interrupts and the data buffers used to properly compress and store the digitized recorded signals is presented. The multi-channel capabilities of the collection algorithm are explained and sample collections are shown. Expected error rates and possible alignment problems are discussed. Limitations of the hardware presently used and possible future improvements are also considered. The chapter ends with a description of a compressed data display routine.

The extraction of motor unit specific information requires the decomposition of the composite EMG signal into its constituent motor unit contributions. This requires the recognition of each motor unit's contribution to the EMG signal. Such an analysis requires pattern or shape recognition techniques. Chapter 4 consists of an introduction to pattern recognition and signal space concepts as they apply to EMG decomposition. Feature space representations, template concepts and distance measures are included. Some of the distance measures used in solving the problem of EMG decomposition and why some were unsuccessful are discussed. The importance of stationary data or a successful technique for tracking the nonstationary data is made evident. Additional information available by the mathematical modelling of the firing rates of the motor units as point processes is explained. How this information is used along with shape information in the final recognition scheme is outlined. The chapter concludes with a full description of the complete decomposition algorithm.

Chapter 5 presents the algorithms used to extract the morphological and rate coding information from the decomposed EMG data. This chapter deals with the assumptions used to account for a less than 100% accurate EMG decomposition and their justification. The algorithm for the extraction of the rate coding information is presented. The technique of filtering gross errors from the individual motor unit firing rate data is included. The creation of running weighted averages of the individual motor unit firing rates is discussed along with the calculation of motor unit firing rate variances. Various parameters calculated and plots created are described. The morphological information extraction technique which is similar to the Macro EMG signal averaging of Stalberg (1980) is explained. Useful parameters of this analysis are presented.

The recording and analysis process was tested by collecting EMG signals from normal subjects. The protocol of these collections is described in Chapter 6. The methods used to evaluate the accuracy of the decomposition and information extraction routines is explained. The accuracy of both the rate coding and the morphological information obtained by the analysis technique for these tests is reported. Comparisons made to similar information obtained by different methods and a summary of the overall system performance are reported.

The value, limitations and possible future uses of the developed procedure are given in a concluding chapter. Future modifications and improvements to the process are mentioned. Special considerations are given to the clinical feasibility of the signal analysis technique. The parameters of the information obtained that merit further study as possible clinical diagnostic indicators are discussed.

CHAPTER 2

EMG RECORDING AND SIGNAL PROCESSING PROTOCOLS

2.1 Introduction

The electrical currents that are created during muscle contraction can be measured with suitable recording electrodes and instrumentation. The recorded potentials are called electromyographic (EMG) signals. EMG signals contain information about the neuromuscular structure from which they were recorded. An understanding of the basis of EMG signals is essential if the information extracted from them is to be accepted. Knowledge of present EMG recording and signal processing techniques and the uses of the information extracted provides insight into the value of EMG analysis.

This chapter first deals with the nature of the composition of recorded EMG signals. It then presents a review of the types of needle electrodes used and the composition of the signals recorded. Some of the methods of signal processing used and the information which is extracted from the EMG signals recorded with the various electrode types, during differing muscle contractions, is then discussed. A new recording and signal processing protocol, which is used to extract motor unit rate coding and morphological information, is then presented. Similarities and differences with present techniques are pointed out. Advantages and disadvantages of the suggested scheme are also discussed.

2.2 Electromyographic Signals

EMG signals can be measured with a variety of electrode configurations and during many varying types of muscle contractions. The EMG signal is the measured potential difference between two electrodes. The electrodes can both be in the active muscle area such as with differential or bipolar recordings. Alternatively, a reference electrode in a nonactive area can be used, as with monopolar recordings. The composition of the EMG signal is dependent on the type of electrodes used, their configuration and the level of muscle contraction. Figure 2.1 is a schematic of the EMG signal sources.

Point electrodes measure the net current field, at specific points, in the interstitial tissue of the muscle. The current field measured is created by the summation of the contributions of all the muscle fibre action potentials (MFAP) present in the muscle (Plonsey 1969). The contribution of each MFAP at the recording site is dependent on the principles of volume conduction. Volume conduction is the term used for the conduction of the currents, created at the membranes of the contracting muscle fibres, through the interstitial tissue of the muscle.

By the use of solid angle geometry calculations and the modelling of the propagating MFAP as a moving dipole, the potential at a point can be determined (Plonsey 1974). This calculation shows that the size of the potential diminishes exponentially as the radial distance from the active muscle fibre or current source to the recording point increases. The conduction of the currents and the solid geometry also

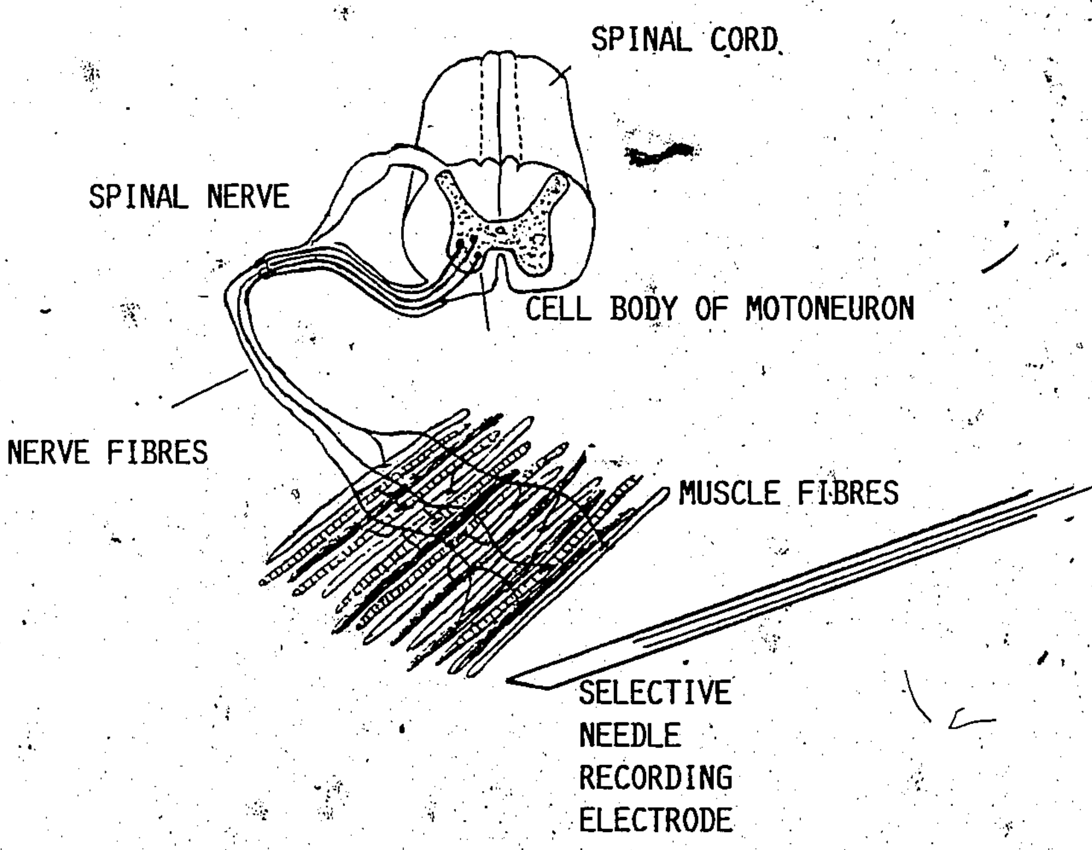


FIGURE 2.1
SCHEMATIC OF EMG SIGNAL SOURCES

cause the recorded potentials to be of lower frequency content as the distance from the fibre increases. This was demonstrated by the classic work of Lorente de No (1947) and Buchthal et al (1957a).

The reduction in frequency content was further investigated by the work of Gath and Stalberg (1977,1978). In the first paper, these authors measured the radial decline of the volume conducted MFAP using a multi-electrode and derived a model transfer function for the muscle tissue. The second paper reported on a study which further verified this transfer function. The transfer function suggested a greater attenuation of the high frequency components of the MFAP, as was shown by the earlier work of the other authors cited. Therefore, the distance to the electrode from the active fibres is of great importance in determining the size and frequency content of its contribution to the net current field at the electrode site. This is due to a reduction in the current densities as the distance away from the membrane increases.

This attenuation in the size of the contribution of a specific MFAP to the current field, at the electrode site, puts a practical limit on the distance from the electrode that a muscle fibre can be and still make an appreciable contribution to the potential recorded. This distance can be termed the uptake distance. The uptake distance, in conjunction with the electrode conducting or recording surface area, results in an effective uptake area for the electrode. The definition of an 'appreciable contribution' is determined relative to ambient noise levels. An appreciable contribution was defined by Gath and Stalberg (1979) as one having a peak potential larger then 0.2 mV.

The calculation of the potentials measured by point electrodes has been discussed above. The net potential field that will be measured by an electrode of finite area is the average of all the potentials existing at its surface (Ekstedt and Stalberg 1973a). Therefore, as the conducting surface area of a recording electrode increases, the amount of spatial averaging of the potentials present at the electrode surface also increases. The increased amount of spatial averaging and the reduction in electrode impedance, with increasing electrode area, tends to cause the signals recorded to be smaller in amplitude and lower in frequency content. However, as the conducting surface area of the recording electrode increases, so does its uptake area. This implies that the number of muscle fibres having an appreciable contribution to the recorded signal may also increase. This tends to increase the amplitude of the recorded signals and offset the effects of increased spatial averaging and reduced electrode impedance, with increasing electrode area. The effects of increased electrode area can then be summarized by stating that the signals recorded will be of lower frequency content and may be smaller in amplitude. Generally, the converse is true if the electrode area is reduced.

The above discussion refers to potentials relative to a distant reference. If a remote reference is not used, the difference in the potentials recorded by each electrode must be considered. Each electrode's size and the separation between them will affect the signals recorded. The term electrode will hence refer to the net configuration.

The nearly synchronous firing of all the fibres of the motor unit causes their MFAP's to summate. A motor unit action potential (MUAP) is the summated response of all the MFAP's of a motor unit which are within the uptake area of the electrode (Gath and Stalberg 1976). Each motor unit will have a unique number of contributing fibres or fibre geometries relative to the electrode. This results in MUAP's of unique shape.

The duration of a MUAP is defined as the time spent above or below a noise related threshold band. MUAP durations are dependent on both physiological and physical factors. The main physiological factors are the number of fibres contributing (in the uptake area of the electrode), the spatial dispersion of the innervation zone, the variance in the conducting velocities of the contributing fibres and the distance from the innervation zone (Buchthal et al 1954b). The physical size and configuration of an electrode determine its uptake area and the amount of spatial averaging it performs. Increases in both of these factors lead to longer recorded MUAP durations (Bucthal et al 1954a). MUAP durations, therefore, vary not only with the type of electrode used, but also with the muscle from which the recording is obtained (Bucthal and Rosenfalck 1955) and the location of the recording site in the muscle (Buchthal et al 1955). MUAP durations can vary from .3 ms to greater than 25. ms. Peak to peak amplitudes of recorded MUAP depend on the number of contributing fibres, their distance from the electrode, the MFAPs' temporal correlation and the electrode's surface area, impedance and configuration. (Buchthal et al 1954a, 1954b). These factors result in a wide range of recorded MUAP amplitudes from 0.1 mV to 20 mV.

As the level of muscle contraction increases, the motor units become more active due to rate coding and more motor units are activated due to recruitment. This results in more electrical activity in the uptake area of an electrode and consequently a more complex signal. The individual motor unit potentials may begin to overlap and summate or cancel each other. The signal may no longer be able to be decomposed into its component action potentials. The converse is true if the level of muscle contraction is reduced.

If the individual motor unit contributions to the EMG can be determined, then the signal can be decomposed and individual motor unit information can be obtained. Alternately, if the individual motor unit contributions to the EMG become superimposed in time and space, then an interference pattern is created. If the individual motor unit contributions to the interference pattern cannot be determined, the information extracted from the signal is generally of a statistical nature and represents all the active muscle fibres in the uptake area of the electrode.

Electrodes with small uptake areas are subject to movement and sampling errors. If the electrode moves slightly, it might be sampling a different muscle area. The amount of needle movement must be checked in all individual motor unit analyses to confirm that the same motor unit population is being studied throughout a contraction. The small measurement areas of selective electrodes require that recordings be taken from many areas to get a representative muscle sample. This requirement is very important in clinical studies.

2.3 EMG Recording Needle Electrodes

2.3.1 Monopolar Needle Electrodes

Monopolar, concentric and bipolar needle electrodes (to be discussed later) were introduced by the work of Adrian and Bronk (1929). The monopolar needle is 0.2 mm in diameter and is insulated but for the last 0.5 mm of its tip. Monopolar needle potentials are usually measured relative to a distant surface reference over inactive tissue. The recording surface area is about .300 mm^2. The resulting effective measurement area or uptake area of the electrode is a circular area of about 2.0 mm diameter (Stalberg 1980). This results in a large number of muscle fibres contributing to the motor unit potentials measured. Durations of MUAP's range from 3 ms to 20 ms, with amplitudes in the .05 mV to 1.0 mV range (Buchthal 1957).

The number of motor units in the uptake area can also be large. Therefore, at moderate levels of contraction the individual motor unit potentials of the many motor units active in the uptake area of the electrode begin to overlap and an interference pattern is created. These electrodes can be used to obtain information about individual motor units at low contraction levels or the muscle as a whole, by analyzing the interference patterns created at moderate contraction levels. This electrode is popular with many clinical electromyographers.

2.3.2 Concentric Needle Electrodes

Concentric needle electrodes are widely used in clinical electromyography. They are also known as co-axial needle electrodes, for like the co-axial cable, they are composed of an outer sheath conductor with an inner conducting wire. The outer and inner conductors are insulated from each other. The outer conductor, the cannula of the needle, ranges from .3 to .7 mm in diameter and is exposed for its entire length. The inner conductor is exposed only at its tip, resulting in an elliptical recording surface .150 X .580 mm. Potentials are recorded between the two conductors. These electrodes have an approximate uptake area of 2.0 mm in diameter. They typically record from 10-15 fibres of each motor unit (Stalberg 1980). This is still a small fraction of the total 200-2000 fibres contained in motor units of normal muscle (Stalberg et al 1976). The outer conductor (cannula) acts as a reference if the needle is substantially inserted into the muscle. Signals similar to monopolar needle results can then be obtained (Lindstrom 1977). However, distant fibres which contribute low frequency components to the monopolar needle recorded signals are cancelled by the shielding effect of the cannula reference and are therefore not present in concentric needle signals (Stalberg 1980). This results in a MUAP with somewhat different characteristics from those obtained with a monopolar needle electrode. Durations and amplitudes of MUAP's measured with concentric needle electrodes are therefore slightly shorter and smaller than MUAP's similarly recorded with monopolar needle electrodes (Buchthal et al 1954).

2.3.3 Bipolar Needle Electrodes

Bipolar needle electrodes consist of two insulated conductors permanently fixed within the cannula of a needle (approximately .7 mm diameter). Signals are recorded between the two conductors exposed only at the needle tip. The difference of the current field, at two active points close together, is measured. This results in signal differencing or differentiation when compared to monopolar or concentric needle signals. The effective uptake area of the electrode depends on the size of the two recording surfaces and their spacing. Very selective recording electrodes can be obtained this way (Andreassen and Rosenfalck 1978, Gath and Stalberg 1976). The signal composition will depend on the selectivity of the recording electrode. Bipolar needle electrodes are generally more selective than monopolar and concentric needle electrodes. Durations of MUAP's recorded with most bipolar needle electrodes are shorter and the MUAP amplitudes are smaller than those of MUAP's recorded with monopolar or concentric needle electrodes. (Buchthal et al 1954a).

2.3.4 Bipolar Fine Wire Electrodes

Bipolar fine wire electrodes were made popular by the work of Basmajian and Stecko (1962). Like the bipolar needle electrode, fine wire electrodes have two insulated wires inserted into the cannula of a needle. The fine wires of this electrode, however, are not permanently fixed to the cannula. After inserting the needle with the wires into the muscle, the needle is withdrawn. The fine wires are exposed at the ends and bent to stick to the muscle mass as the needle is pulled out. The recording surface areas of the fine wires are adjustable, but their separation in the muscle is not controllable. This results in variable uptake areas. Although similar to bipolar needle electrodes, they usually have larger recording surfaces and interelectrode spacings, making them less selective. Bipolar fine wire electrodes are generally less selective than monopolar or concentric needle electrodes as well. Ranges for MUAP durations and amplitudes will depend on the specific electrode configuration implemented. Basmajian and Cross (1971) report MUAP durations ranging from 1.0 ms to 12.4 ms. Variations of this needle type have been used by other researchers for various studies (Costa et. al. 1977 and Clamann 1969).

2.3.5 Single Fibre Needle Electrodes

As the name suggests, the single fibre electrode is selective to the point of being able to measure single muscle fibre action potentials. The initial work with single fibre electrodes was carried out by Ekstedt and Stalberg (Ekstedt and Stalberg 1973b, Stalberg and Ekstedt 1973). These electrodes consist of a 0.5 mm diameter needle with an internal .025 mm diameter conductor brought out through a side port in the cannula some 3 mm from its tip. The potentials are measured from this small surface relative to the cannula. Due to the shielding of the cannula, the uptake area is semi-circular with a diameter of .6 mm (Gath and Stalberg 1979). The motor unit action potentials recorded have contributions from only 1-2 muscle fibres (Stalberg 1980) and can record from up to 30 motor units simultaneously (Gath and Stalberg 1979). The MUAP'S recorded, range in amplitude from .2 mV to 25 mV, although typically they are below 5 mV (Stalberg 1982). Durations can be less than .3 ms (Stalberg 1980), but are typically 1.0 ms with .1 to .15 ms peak to peak rise times (Stalberg 1982). Durations of up to 3 ms have also been measured. The amount of superposition of the MUAP in the composite signal is small due to their short duration. This results in the ability to record open signals, where each motor unit component can be determined, even at high levels of muscle contraction.

2.3.6 Macro EMG Signals

Macro EMG signals, introduced by Stalberg (1980), are the synch averaged, cannula responses, of modified single fibre needle electrodes. The individual motor unit responses recorded by the single fibre electrode are used as synch triggers to average the concurrent activity measured by the needle cannula. Synchronized averaging extracts the individual motor unit contributions to the cannula recorded interference pattern (Stalberg 1980). Macro EMG electrodes differ from single fibre electrodes in that only the last 15 mm of the cannula is exposed and the single fibre recording surface is placed 7.5 mm from the tip (Stalberg 1983).

Acquiring macro EMG signals requires the recording of two channels of EMG. On one channel, recording is done between the cannula and a remote reference. A subcutaneous monopolar needle or a surface reference is used. The other channel records between the .025 mm diameter single fibre surface and the cannula. Because of the large recording surface of the cannula, it is capable of measuring potentials from a larger portion of the motor unit than monopolar or concentric needle electrodes. Hence, it contains information not available by more selective recording techniques (Nandedkar and Stalberg 1983).

2.4 Signal Processing Techniques

2.4.1 Introduction

Using mostly monopolar or concentric needle electrodes, clinical electromyographers study the electrical activity of muscle. This analysis ranges from electrical activity elicited spontaneously, such as fibrillation and fasciculation potentials, to the study of single MUAP shapes, to the analysis of the full interference pattern recorded from the active muscle. Physiological researchers have used mostly bipolar or fine wire bipolar electrodes to study the discharge characteristics of various muscles under various contraction protocols. This section contains a review of the types of clinical studies performed and the types of analysis used to extract relevant muscle information. It concludes with a review of the work done in the area of motor unit rate coding and recruitment. These reviews are not exhaustive in nature. Nonetheless, they are intended to be representative of the work performed in these specific areas.

2.4.2 Spontaneous Electrical Activity

A healthy muscle has no electrical activity while at rest (Buchthal 1957). However, some pathological muscles do produce spontaneous electrical activity during rest which can be recorded with needle electrodes (Denny-Brown 1949). Daube (1982) reviewed the various types of activity which can be recorded. The two main types of spontaneous activity are fibrillation potentials and fasciculations. Fibrillation potentials are thought to be caused by hyperactive denervated muscle fibres. Fasciculation potentials are the result of the unsolicited firing of complete motor units. The presence of spontaneous activity usually signals a clinically abnormal muscle, but the etiology of the disorder can not be defined by this activity.

2.4.3 Individual Motor Unit Action Potential Analysis

Individual MUAP's recorded with concentric or monopolar electrodes during weak levels of contraction have been analyzed for the presence of clinically useful information (Buchthal and Clemmensen 1941). Buchthal and Pinelli (1952) established a technique for measuring the individual MUAP's amplitude, duration and number of phases. These parameters are believed to have direct motor unit morphological determinants which change with disease. These parameters also vary widely in both normals and patients with neuromuscular disorders and must therefore be treated from a statistical view point.

If the rise time is sufficient to discount volume conduction effects, amplitude can reflect the size of the motor unit. Duration reflects the spatial dispersion of the end-plate region, the mean value and variance of the conduction velocities of the fibres of the motor unit, and therefore, the mean value and variance of their diameters. Most importantly, duration reflects the size and spatial dispersion of the motor unit. The number of phases reflects the homogeneity of the motor unit. If the number of phases is increased, this indicates a fractionation of the motor unit. Therefore, changes in these measures, assessed statistically, indicate the morphological changes occurring as a result of neuromuscular pathologies.

In order to obtain a sufficient statistical sample size and, to have data representing the whole muscle, twenty different MUAP's from several different muscle areas are recorded and analyzed. Measurements of duration and number of phases are found to be particularly useful clinical indicators of the etiology of various muscle and motor neuron diseases (Buchthal and Pinelli 1953a, 1953b). Summarizing their findings, it is generally found that the durations of MUAP's are shortened and the number of phases are increased for myopathies, while MUAP duration is lengthened and the number of phases are normal for neuropathic problems.

This analysis, introduced by Bucthal and his co-workers, though clinically useful, was not widely applied due to the large amount of time required for the collection and measurement of the twenty suitable MUAP's. Lee and White (1973) developed a computer algorithm to perform the measurement more quickly and accurately. However, the problem of collecting the required number of suitable MUAP's, free of background noise, still remained.

A system of averaging MUAP's from the same motor unit, which suppresses background noise and interference from other simultaneously firing motor units in the uptake area of the recording electrode, was introduced by Lang and Tuomola (1974). Averaging of the MUAP's from a single motor unit to improve definition has also been performed by Partanen and Lang (1982) in their study of MUAP parameters in polymyolitis. Recently, Falck (1984) reported the use of a special electrode with both single fibre and concentric needle recording surfaces. The single fibre potentials recorded are used as synchronization triggers for averaging the concentric needle recorded potentials. The resulting average was a more precisely defined MUAP of a single motor unit than can be reproducibly obtained from a single firing of the motor unit.

Stalberg (1984) has reported a technique of template matching and averaging of MUAP's to extract a single, pure MUAP from the background noise. The first eight MUAP's from a motor unit are chosen by trigger level and displayed. These potentials are then used to automatically, or by operator control, choose the most representative one as a template. When eight MUAP's suitably similar to the chosen template have been found, they are averaged. Subsequent measurements and analysis are then carried out. If continuous potential selection is performed, by setting the trigger level near the level of the ambient noise, small amplitude MUAP's can be chosen, by the operator, as the initial template and subsequently analyzed. It is pointed out that if lower amplitude potentials are to be analyzed, rise time constraints should be set to assure that volume conduction effects are not appreciable factors in the parameters measured.

Andreasson (1984) has developed a computer based collection and measurement system. The collection algorithm is based on a pattern recognition and template matching scheme. The system automatically selects suitable MUAP's from a population of active motor units. The force levels for these contractions are such that a full interference pattern is not created. The initial potentials are used as templates and successive potentials are matched to these templates. The MUAP's are classified as belonging to the template with the least total square difference. Classification of a MUAP to a specific template is equivalent to assuming that the MUAP originated from the same motor unit as it's template. Classified MUAP's are stored in buffers with their respective templates. When, for a particular motor unit there are three very similar MUAP's each is assumed noise free. They are averaged and measurements of the averaged result are performed automatically. The algorithm continues until a sufficient number of different MUAP's have been measured. Statistical analysis of the measurements is also performed and displayed. This system is now commercially available. The future common use of this system in modern clinics is expected.

McGill and Dorfman (1983) have also developed an analysis scheme which extracts averaged MUAP's from populations of active motor units. The averages are based on synch trigger spikes corresponding to the individual motor unit firings. The trigger spikes are obtained from the decomposition of the high pass filtered interference pattern recorded during moderate muscle contraction. The decomposition extracts the firing times of each of the dominant motor units composing the measured interference pattern. Up to fourteen motor units can be resolved from the composite EMG. The averaged MUAP's are then obtained by using these individual motor unit firing times to synch average the original unfiltered interference pattern. The averaged MUAP's are then measured and the data statistically analyzed. This method has the advantage of being able to extract those MUAP's which are active only during high levels of contraction, which might have significant clinical value in some situations. Normative data for this technique is presently being compiled by the authors.

Coatrieux et al (1983) proposed a pattern recognition scheme for the automatic classification of recorded MUAP's. The basis of comparison is representative populations of MUAP's from normal and pathological muscle. The program then automatically classifies a subsequently recorded MUAP as normal or pathological, based on a comparison of characteristic features of its shape with those of the representative populations. Clinical success of this procedure has not yet been reported.

Analysis of single MUAP's provides morphological information about the individual motor units. If a statistical population of MUAP's from different areas throughout the muscle is analyzed, morphological information representative of the whole muscle can be obtained.

Representative morphological information can also be obtained by analyzing the interference patterns recorded with suitable electrodes during moderate to high levels of force. The next section discusses the basis of the interference pattern and techniques of extracting useful information from these patterns.

2.4.4 Interference Pattern Analysis

An interference pattern (IP) is created when the individual MUAP components of the interstitial current field, as recorded by an electrode, overlap in time and space. The result is a composite signal in which the component parts are either impossible or at least very difficult to decipher. Information specific to individual motor units is not available. However, information, in a general sense, about the size and interactions of the motor units represented in the composite signal, is available in the IP.

The composition of the IP is dependent on the number of active motor units, their size, spatial distribution and firing times. The random nature of these factors result in the IP being a stochastic process. The IP is, therefore, best described by statistical parameters. The IP recorded is also dependent on the type of electrode used, its position in the muscle, the muscle and the level of contraction. These factors must be accounted for in any successful analysis scheme.

The information contained in the IP is of a relative nature and can be extracted by comparing the responses of different muscles during similar force producing contractions. The compositions of the IP's reflect the relative number, size and firing rates of the active motor units of the tested muscles. This comparative information can indicate the state of health or disease of a muscle.

A muscle composed of a certain number of motor units with given size and spatial distributions, produces a specific level of force through a certain interplay of recruitment and rate coding. This interplay results in the creation of a current field, which when recorded by a suitable electrode, results in an IP. The IP will have specific statistically describable features. Changes in the number of motor units, their size, or spatial distributions, will change the interplay of recruitment and rate coding performed for a specific level of contraction. This should be reflected in the values of the statistical parameters used to describe the IP. This dependence of the IP on discharge rates and the level of recruitment has sometimes led to it being called a discharge or recruitment pattern.

The type of electrodes usually used to record IP's are concentric and monopolar needles. These needle electrodes are used because of their wide clinical acceptance and for the ease, at relatively low levels of contraction, with which IP's can be recorded. Due to the limited uptake area of these types of electrodes and the statistical nature of the IP descriptive parameters, several collections and measurements must be performed in different muscle locations.

Early attempts at describing the IP were strictly of a qualitative nature. The IP was described simply as full or open (Bucthal 1957). The first attempt at quantifying the IP was by Willison (1963). He described the IP by the number of turns per second and by the mean amplitude of the turns. A turn was defined as a potential reversal having an amplitude greater than .1 mV and the mean amplitude as the total absolute amplitude of all reversals divided by the number of reversals. The analysis was done at different standard levels of force. This analysis attempted to measure a generalized firing rate and MUAP amplitude. The analysis was found to be able to differentiate between normal and myopathic patients (Willison 1964).

Willison's original analysis was done manually with photographic film and specialized mechanical equipment. The process was then implemented using electronic circuits and counters (Fitch and Willison 1965, Fitch 1967, Hayward and Willison 1973). The accuracy of the electronic analyzer and the variation of the results with level of force production was also investigated (Rose and Willison (1967). The results of this study showed that the electronic equipment was faster and suitably accurate. It also pointed out the importance of maintaining standard levels of force throughout the data collection.

Other early methods of quantifying the IP are also reported. Colston and Fearnley (1967) measured the integral of the amplitude per second as well as a turns count, at a standard two kilogram force level. Fusfeld (1971) electronically measured the average wave duration by triggering on zero crossings. This was believed to be a similar analysis as Bucthal's measurement of MUAP duration. The author found reduced average wave durations in myopathic muscle. A computer based system which did both IP and single MUAP analysis was developed by Kunze (1973). Kunze measured the integral of the amplitude per second, the potential time per second and the number of phases (similar to number of turns) per second. He produced various plots of these variables and claimed the ability to differentially diagnose myopathies and neuropathies.

The use of computers for this type of analysis was studied by other researchers as well. The output of the electronic equipment introduced by Fitch was fed into a special Biomac 500 computer in a later study (Dowling, Fitch and Willison 1968). The application of the computer allowed not only the standard measurements to be made, but also histograms of the times between turns and the amplitude per turn to be compiled. This additional information was found to be very useful in the differentiation of neuropathic and myopathic patients. Kopec et al developed a specialized computer to investigate the IP. The system created histograms of mean duration, mean phase duration and mean number of phases for up 1024 collected MUAP's. The technique is similar to that of Buchthal, except that the MUAP's are defined in the IP and are not measured in isolation. Hirose and Sobue (1972) and later Hirose et al (1974a) also performed the Willison technique using a computer for the measurement and statistical evaluation. These authors found that the technique had successful clinical yields for myopathic patients (Hirose et al 1974). Hirose et al (1975) found that if the definition of a turn was lowered to .05 mV and the muscle was contracting at maximum voluntary effort, that a better separation between normal and myopathic patients could be obtained.

The effects of level of contraction, sites chosen in the muscle, number of sites chosen and contributions of other muscles to a produced force, on the measured Willison parameters of the IP was investigated by Fuglsang-Frederiksen and Mansson (1975). This study suggested that the chosen muscle sites be evenly distributed, that at least ten sites be investigated, and that antagonist activity during force production did not significantly affect the measured IP parameters. More importantly, they proposed that the level of contraction should not be a fixed level of force, but instead be a fixed proportion of the maximum voluntary contraction possible. This was intended to account for the different relative strengths of the tested subjects. This protocol would then have each subject exerting an equal relative amount of effort. In a subsequent study, this modified Willison technique, complemented with single MUAP measurements, resulted in 90% accurate clinical diagnosis (Fuglsang-Frederiksen et al 1976). The ratio of the number of turns to the mean amplitude was found to be clinically most useful.

In their review of quantitative EMG practices, Boyd et al (1976) stated that these techniques were not widely used clinically. This might have been due to the disparity of the reported accuracy of these techniques. Valli et al (1976), in a study of the effectiveness of single MUAP measurements and the Willison technique for the detection of carriers in Duchenne muscular dystropy, found the latter to be successful in only two out of seventeen cases. While Hayward (1977) and Hayward and Willison (1977), using a only slightly modified Willison technique, showed reproducible changes in measured parameters due to the effects of age in normals and in patients with chronic denervation. With such discrepancies in the success of the existing techniques being reported, alternate ways of analyzing the IP were developed. Fusfeld (1978) electronically measured zero-crossing peak rates, negative wave durations and wave rise times. He then proposed a method using linear discriminants to determine the clinical state of a muscle (Fusfeld 1982).

The dependence of the measured parameters of the IP on the level of contraction can be reduced by calculating the ratio of the logarithm of the number of turns to the logarithm of the mean amplitude of the turns (Cenkovich 1983). This ratio was found to be independent of the force of the contraction. Its clinical value is yet to be determined. Stalberg et al (1983) avoided the need for standard contraction level by plotting the number of turns versus the mean amplitude of the turns for various levels of muscle contraction. Using a population of normal subjects, an area in the plot or 'cloud' is defined. Patients having more than two responses outside the cloud area, on the same side, are defined as abnormal. The method is reported to have high clinical yields; with myopathic and neuropathic responses falling in opposite areas of the 'cloud'.

All of the IP analysis methods described above deal with time domain representations. However, all of the parameters used can be conceptualized in a frequency domain context. Frequency domain studies of the IP were first proposed by Richardson (Walton 1952), who proposed a ratio of the power in the recorded signals above and below 400 Hz respectively. Walton (1952) used an audio frequency spectrometer to measure the IP and found an increase in the high frequency components of IP's recorded from patients with muscular dystrophy. Fex and Krakau (1957) however, could not reproduce Walton's results.

The frequency spectra of EMG signals collected from muscle stimulated at fixed rates showed some differentiation between normal and myopathic muscles (Cenkovich and Gersten 1963). This study showed that the individual MUAP durations and firing rates influenced the EMG spectra. These authors proposed that a hyperbolic curve be used to test for significance of high frequency harmonic elements in the spectra. The equation of the hyberbolic curve was determined by half of the maximum product of the frequency components ordinate and abscissa values. High frequency components exceeding this hyperbolic curve were deemed significant. This hyperbolic limit was determined empirically based on the EMG spectra obtained. It was found that only the pathologically short potentials of the myopathic muscles consistently exceeded this threshold and it could therefore be diagnostically useful. Later, Gersten et al (1965), studied EMG spectra from normals and patients with myopathic and neuropathic symptoms. Auditory feedback was used to maintain relatively constant firing rates and some clinical yield was reported.

Frequency analysis of the IP was also performed by Larsson (1968) in a study with patients with neuromuscular disorders. This work clearly showed increased high frequency content in EMG spectra obtained from myopathic muscle and a shift to lower frequency content of the EMG spectra with neuropathies. These results proved the value of this type of analysis. Discrepancies in the spectra of EMG's reported for patients with lesions of the peripheral motor nerve were explained as being related to the duration of the clinical symptoms (Larsson 1975).

In summary, it has been clearly demonstrated that the analysis of the recorded IP can yield useful information in the clinical assessment of muscle. Expected intra and inter patient variances, along with 'normal' mean values, must be determined for each descriptive parameter used for each specific clinical recording and muscle contraction protocol. The time required to perform the data collection and analysis has limited the use of quantitative techniques to special clinical patients (Daube 1982). It is hoped that with further development of computer based collection and analysis systems that time will no longer be a factor.

2.4.5 Single Fibre EMG

Single fibre EMG (SFEMG) is the collection and analysis of EMG signals recorded with the single fibre needle electrode previously described in section 2.3.5. The analysis is performed to obtain information about normal and pathologic motor units. The filter settings used for SFEMG are typically 500 Hz at the low end to reduce the far field contributions to the recorded signals and 10 KHz at the high end to suitably reproduce the single fibre action potential.

SFEMG is used to measure motor unit fibre densities (Stalberg and Thiele 1975). A SFEMG recorded MUAP is composed of the contributions of at most only a few muscle fibres in the motor unit. The number of contributing fibres can very often be determined by the shape of the recorded MUAP. The average number of fibres thought to be contributing to a recorded MUAP is taken as a measure of the fibre density of a motor unit. This average is obtained by sampling twenty different sites in the muscle.

The consistency of neuromuscular transmission in motor units can be studied by measuring neuromuscular jitter. Recordings are taken from a motor unit whose MUAP has the potentials of two distinct fibres, during a constant low force muscle contraction. The variation of the interval between these two potentials is the jitter. The jitter is bimodal and gaussian distributed (Thiele and Stalberg 1974). This variation is subject to slow trends which can affect the results of a study and is therefore expressed as a mean consecutive difference (MCD) (Ekstedt et al 1974). A study done on patients with myasthenia gravis showed that they had significantly higher MCD values than normals (Stalberg et al 1974). If the second potential is absent for a firing of the motor unit, complete neuromuscular transmission failure for that fibre, has occurred. Complete neuromuscular transmission failure or blocking, is rare in normal muscle and is an indicator of neuromuscular transmission problems.

The selectivity of the SFEMG also lends itself to the study of firing patterns of motor units. Stalberg and Thiele (1973) studied the variability of motor unit firing during constant force muscle contractions. They found that the variance of the firing rate was mostly dependent on fluctuations in the motorneurons depolarization and only partially due to threshold changes. They therefore suggested that firing rate variances might be of some clinical use. SFEMG needles were also used in attempts to distinguish tonic and phasic firing patterns of motor units (Stalberg and Antoni 1981).

2.4.6 Macro EMG

Macro EMG as described earlier in section 2.3.6, is a new EMG recording technique introduced by Stalberg (1980). The Macro EMG is the result of synchronously averaging the electrical fields sensed by the cannula of a needle electrode. The synchronization is provided by a single fibre recording surface located in the plane of the cannula surface. The MUAP's recorded by this selective recording surface are used as pulses to trigger the averaging process.

At low levels of contraction, firings of a single motor unit can be obtained for triggering the averaging of the concurrent cannula response. The synchronous averaging extracts the individual motor unit contributions to the cannula recorded signal. The noncoherent background activity averages toward its zero mean value. The resulting average of the potentials recorded by the cannula is the macro motor unit potential (macro MUP).

Macro MUP's are the average motor unit response over the entire motor unit territory, as seen by the cannula. Therefore, they contain information not present in other needle recorded MUAP's. Based on models of single fibre action potentials and needle cannula recording properties, the macro MUP was simulated (Nandekar and Stalberg 1983). The simulation was performed to investigate the effects of several factors on the shape of the macro MUP. The factors studied were:

number of fibres in a motor unit, fibre diameters, end plate scatter, nerve branch delay, motor unit territory and electrode position. It was found that the number of fibres and the mean fibre diameter acted as gain factors for the MUP at all needle positions. It was also found that the macro MUP was sensitive to the location of the recording site. Near the end plate, the MUP depicted end plate scatter. Away from the end plate, the macro MUP displayed the fibre diameter distribution. Most importantly, it was determined that the area of the macro MUP was more indicative of the motor unit size than was its peak to peak amplitude.

Stalberg and Fawcett (1982) collected MUP's from several different muscles of normal subjects of varying ages. Their data is to be used as a data base for normal subjects. Results for patients with various clinical symptoms have also been obtained. Stalberg (1983) reports some of the general characteristics of the macro MUP recorded in patients with different clinical symptoms. In primary myopathies, the macro MUP's are generally lower in amplitude than normal results. The shape of macro MUP's often become more fractionated. The area and amplitude of the macro MUP is typically increased in conditions of reinnervation. In motor neuron disorders, the macro MUP amplitudes range from normal to increased, depending on the disease duration and rate of progress. Further assessment of the value of macro EMG as a routine clinical EMG practice and of its use in conjunction with SFEMG is presently being carried out (Stalberg 1983).

The mathematical and computer simulations showed that the shape of the macro MUP is determined by the morphology of the motor unit from which it is recorded. Therefore, techniques aiding in clinical diagnosis via automatic recognition of shape features of macro MUP's are being developed. Some initial work in this area has been done by Nandekar and Sanders (1984) and by Nandekar et al (1984). This work consists of representing macro MUP's by special orthonormal basis functions, which are determined from a suitable selection of normal macro MUP's. Macro MUP's are classified as abnormal if they fall outside a 98% probability cluster in the feature space of the normal population. A study is considered abnormal if more than 2 out of 20 macro MUP's are classified as abnormal. Work of this nature, in which computer based systems aid the clinician in the investigation and diagnosis of patients, is of great value and shows much promise.

2.4.7 Scanning EMG

Scanning EMG is a recording technique which investigates the organization of a motor unit. By moving an EMG electrode through the motor unit, a continuous scan or `electrophysiological cross section' is obtained (Stalberg and Antoni 1980). A single fibre electrode is positioned in the muscle to record MUAP's from a voluntarily, consistently active, low threshold motor unit. A separate concentric needle electrode is inserted close to the single fibre electrode. The MUAP's which are recorded by the single fibre electrode are used as synch triggers to average the activity recorded by the concentric needle electrode. A scan of the motor unit territory is then obtained by moving the concentric needle, in step intervals, through the motor unit, while recording and storing a synch averaged concentric needle MUAP at each location. Specialized computer processing and display algorithms then produce raster scans or grey scale plots of the scan results.

These plots show the electrical activity recorded as the needle was drawn through the motor unit. The consistency and extent of the motor unit territory is evident. Fractionation of the motor unit is seen in some patients with muscular dystrophy. The technique, with the modification of recording from the cannula of the concentric needle, has also been used to show the stability of macro MUP's, with needle position, within the motor unit.

2.5 Rate Coding and Recruitment Studies

Discharge patterns of single motor units, or groups of active motor units, during various voluntary muscle contractions have been studied by the use of selective needle electrodes. The firing of individual motor units can be determined by the unique shape of their MUAP's as recorded in an EMG signal. Firing rate studies involve the time intervals between the firings of the same motor unit or inter pulse interval (IPI). These IPI's are measured and their statistical nature is determined. Estimates of the mean motor unit firing rate and firing rate variances can be obtained by statistical analysis of the IPI's. The way in which the firing rates of the motor units change, with changing or constant muscle force, is termed rate coding.

The investigation of recruitment is a more difficult task. The total number of motor units active at any one time must be determined. Therefore, the degree of recruitment during a contraction is measured in relative, rather than absolute, terms. The force thresholds at which motor units are recruited and the size of recruited motor units have been studied.

Research into discharge patterns of motor units has been performed mainly by physiologists. The clinical use of this type of EMG analysis has not been widely reported in the literature. Some work into the possible use of this information has, however, been done (Freund et al 1973, Stalberg and Thiele 1973, Prochazka et al 1973).

The statistical properties of motor unit firings have been investigated. The analysis of histograms of the IPI's have shown that the firing of a motor unit is a nonstationary, independent, gaussian renewal process (Clamann 1969). The variance of the IPI is found to be a function of its mean (Person and Kudina 1972, Clamann 1969), with the variance increasing along with the mean. Slight, but not significant, serial correlation of the IPI's has been reported by De Luca (1979). It has been suggested that the nonstationarity of the IPI's is a function of the force level and time duration of a contraction (De Luca and Forrest 1973).

Motor units are recruited and decruited based on a certain force thresholds. Once a motor unit is recruited, it remains active throughout a contraction or until the force drops below its decruitment threshold (De Luca and Forrest 1973, De Luca et al 1982a). Motor unit recruitment follows the size principle introduced by Henneman (1965).

This states that larger motor units are recruited at higher levels of force. This was also found by (Milner-Brown et al 1973b) in hand muscle. They proposed that the force contribution of newly recruited motor units was such that it was a fixed ratio of the total force being produced by the muscle. Grimby and Hannerz (1968), however, showed that the recruitment order was dependent on proprioception and the velocity of the contraction.

Firing rates reported in the literature have a wide variance. The rates quoted vary with velocity and level of contraction and with the muscle being studied. Minimal rates are in the 5-10 pulses per second range, while maximum rates range to 100 pulses per second (De Luca 1979). Milner-Brown et al (1973c), measured a linear increase in firing rate with force increase, independent of the recruitment threshold. They also found that a change in the rate of force increase changed this result. In a study of various muscles contracting at maximum effort, it was found that the mean firing rates for each muscle varied roughly in proportion to their respective twitch contraction and half relaxation times (Bellemare et al 1983). These authors proposed that the range of firing rates of each motor unit pool is limited to that which is sufficient to produce maximum force in each motor unit.

Studies performed with selected force rates in different muscles have suggested various strategies of recruitment and rate coding interplay. Bigland and Lippold (1954), recording from hand muscles at low levels of force, concluded that most of the muscle's force increase was produced by recruitment of new units. They reported little rate coding for the increase of force. Milner-Brown et al (1973c) found that for the first dorsal interosseous muscle recruitment was primarily used to increase force at low levels, but at higher levels of force, rate coding was the primary control element. Kukulka and Clamann (1981) compared the recruitment rate coding interplay in the adductor pollicis and biceps brachii. They found similar control mechanisms to Milner-Brown et al (1973c) for adductor pollicis. However, for the biceps brachii it was found that both recruitment and rate coding were used relatively equally to control force at levels up to 90% of maximum voluntary effort.

De Luca et al (1982a) also stated that the interplay of recruitment and rate coding was dependent on the muscle. Their study analysed signals recorded from the deltoid and first dorsal interosseous muscles during triangular force-varying isometric contractions, reaching 40 and 80% of maximum effort. "It was seen that a highly ordered recruitment scheme, based on the motor unit excitability, exists in the muscles studied. The firing rates at recruitment were consistently higher than at decruitment. The differences in the interplay of recruitment and rate coding found for these muscles was similar to those published by Kukulka and Clamann (1981) for the adductor pollicis and the biceps brachii."

De Luca et al (1982b) performed cross-correlation analysis between force and firing rates of the individual motor units and between the firing rates of the individual motor units, using the data extracted by De Luca et al (1982a). These analyses showed the existence of a common drive for active motorneurons in a single muscle pool, and that rate coding leads force production in a size related motor unit control scheme.

2.6 A New Recording and Signal Processing Protocol

The above review of EMG recording and signal processing techniques reveals the wide clinical use of motor unit morphological data. The lack of the clinical use of specific motor unit temporal or discharge pattern information is also evident. The clinical value of temporal data has not been thoroughly investigated. Nonetheless, it is logical to expect differences in the way neural control is effected with various neuromuscular disorders. Changes in the neuromuscular structure would cause such adaptation in the methods of controlling muscle force production. These changes would then be reflected in the results of a discharge pattern analysis. Temporal data might also be useful in determining the existence of central nervous system disorders. The quantification of the firing patterns could indicate tremor or other pathologic conditions of supraspinal origin.

The research performed to study the neural control of muscle has primarily been done by physiologists. The techniques involved in this type of research presently require the manual decomposition of the EMG signal into its component parts or operator-aided computer decomposition (LeFever and De Luca 1982). Both of these methods require too much time to be clinically feasible. The inability to readily measure temporal aspects of the individual components of the EMG, and to estimate the amount of rate coding and recruitment being effected, precludes the use of varying neural control strategies as clinical indicators of pathology.

A new recording and signal processing protocol has been developed. It is an initial attempt at developing a tool which would eventually be used in a clinical setting to aid in the diagnosis of neuromuscular disorders. The recording and signal processing protocol is designed to extract both motor unit specific temporal and morphological information, as automatically and accurately as is practical, in limited time. The time limit is dependent on what is deemed practical in a clinical setting. This tool may also be used to facilitate further physiological research in this area. A general description of the protocol follows.

Signals are obtained using a standard single fibre needle electrode, during constant force or force varying isometric contractions. Two channels of EMG data, along with a force transducer output, are recorded and stored. One channel records the potentials measured between the single fibre surface of the needle and a distant surface reference. The second EMG channel records the response seen between the needle cannula and the same distant surface reference. The EMG signals are suitably differentially amplified and band pass filtered. The pass band of the single fibre channel is 500 Hz to 5 KHz, while the cannula response has a pass band of 8 Hz to 1.25 KHz.

A force target range, as well as the subject's actual force output, as measured by a force transducer, are displayed on an oscilloscope. The force target range is set at the desired constant level for constant force contractions. Alternatively, the force target can be swept through a triangular force pattern of 30 seconds duration. The subject is instructed to perform a smooth contraction with a force output within the force target range. Force ranges to 50% maximum voluntary effort are performed. Figure 2.2 shows, schematically, the recording set up.

The neural control information is obtained by the decomposition of the signal, recorded by the selective surface of the needle, into its component motor unit action potential trains (MUAPT's) by an interactive, semi-automatic computer algorithm to be described in complete detail in Chapter 4. The IPI's of the individual MUAPT's are analyzed to produce the rate coding information. The motor unit morphological information is extracted by synchronously averaging the cannula response using the individual decomposed MUAPT's as triggers. This results in macro MUP's, similar to those described by Stalberg (1983), for each motor unit found in the composite signal. The various force isometric contractions are used to elicit differing states of neural control. These states can then be studied by this technique, which can track motor unit firing rates and measure the relative sizes of the active motor units analyzed.

Due to the selective nature of the single fibre electrode, needle movement must be monitored. This is to ensure that the population of motor units being sampled remains constant and that the recorded MUAP's shapes do not change drastically. Needle movement is assessed by the protocol used in obtaining a successful data collection. The slope and amplitude of the selective needle signal is electronically monitored. Amplitude and slope criteria are set to ensure that a recording is suitably close to at least one muscle fibre of the motor units studied. Amplitude values greater than 1 mV with a slope greater

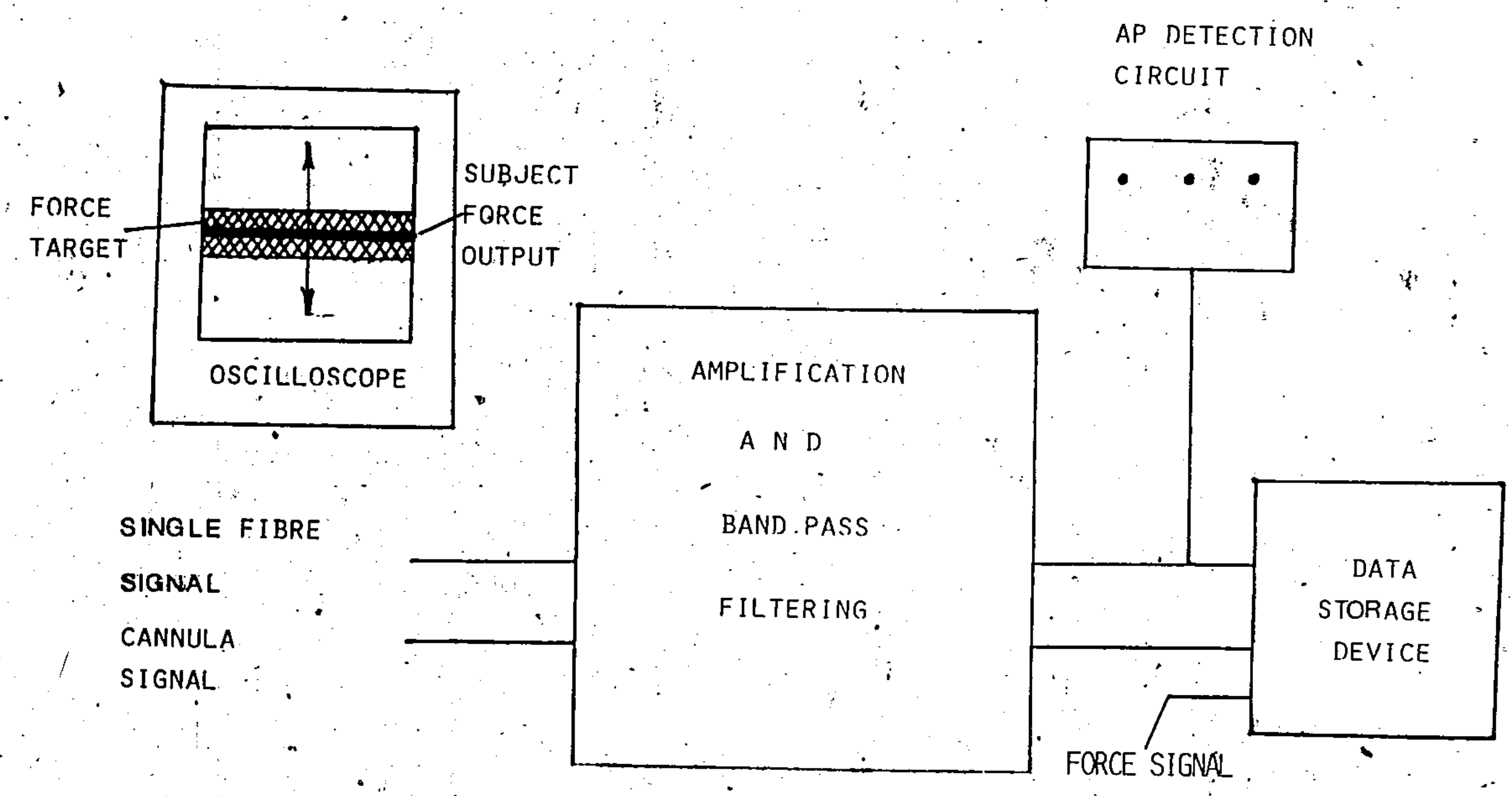


FIGURE 2.2
GENERAL DATA REQUISITION SET UP

than 6 V/S are typical limits used. The movement constraint, which states that these amplitude and slope criteria must be maintained throughout the contraction, is then applied. A contraction is not started until, at minimal force, this constraint is satisfied. If this constraint is not met throughout a contraction, excessive needle movement is assumed, the data is rejected and another contraction is attempted. The presence of suitable amplitude and slope is indicated by flashing lights included with the electronic monitoring hardware. A more complete description of this hardware can be found in Appendix 1.

This technique is similar to combining SFEMG and Macro EMG. The recording of the potentials of the single fibre channel relative to a distant surface electrode will make these recordings less selective than conventional SFEMG. This increase in uptake area does not significantly alter the recorded MUAP shape, but does increase the potential number of active motor units sampled. The reduced high frequency cutoff of the band pass filters compared to conventional SFEMG also does not drastically change the recorded MUAP shapes. It does allow a lower sampling rate to be used. The use of a SFEMG needle instead of the slightly modified Macro EMG needle results in differences in the macro MUP's obtained. The macro MUP changes, however, are not large. The standard SFEMG needle was chosen because it is clinically more easily obtained.

The use of the SFEMG needle produces open signals with few superpositions of the MUAP's from different motor units. Even at contraction strengths above 50% maximum voluntary effort, the number of superpositions with this protocol is less than 10%. This is due to the short durations of the measured MUAP's. The relatively few number of superpositions keeps the decomposition task tenable and the subsequent time required acceptably low. If the number of superpositions becomes too high (above 20%), the decomposition time becomes excessive.

Thus, the main advantage of this protocol is that the signals recorded by the single fibre surface can subsequently be decomposed in suitable time and with sufficient accuracy to be clinically useful. The protocol introduced also has the advantage of extracting individual motor unit rate coding information and their corresponding macro MUP's. This allows motor unit size to be correlated with firing rates. The decomposition allows the macro MUP's from high threshold units to be reliably obtained. The primary disadvantage of the recording technique is the effect on the recorded single fibre signal to minute needle movements. Criteria and constraints built into the protocol attempt to overcome this, but visual verification of the consistency of the data by the operator at the start and end of a collection, is necessary.

Signals produced by this protocol during a variety of force varying isometric contractions are presently recorded on FM tape then digitized and stored on computer. The single fibre signals are then decomposed by a operator assisted computer algorithm. The decomposed SFEMG data along with the cannula responses are then processed to extract temporal and morphological information. The next three chapters deal with these processes.

CHAPTER 3

DATA COLLECTION AND COMPRESSION

3.1 Introduction

The new recording protocol discussed in the previous chapter proposed the recording of EMG signals from both a selective needle surface and the needle cannula, relative to a distant reference. These recorded EMG signals must be collected to be analyzed by a computer system. The term collected refers to the sampling, digitizing and storing of the data. The EMG signals recorded by the selective needle surface are sparse in nature. This is to say, that for the majority of the time, the recorded potential is simply ambient electrical noise. An example of a continuous collection of this data can be seen in Figure 3.1.

The events of importance for the new recording protocol are the MUAP's of the active motor units as recorded by the selective needle surface and the concurrent activity recorded by the needle cannula. Therefore, the two channels of data must be simultaneously acquired. The times of the MUAP occurrences are also important. The remainder of the electrical activity is of no use and need not be stored.

The extraction and storage of only the MUAP's and their times of occurrence during a data collection is termed data compression. Compressed selective needle recorded data can be seen in Figure 3.2. The numbers between the MUAP's represent the elapsed time in

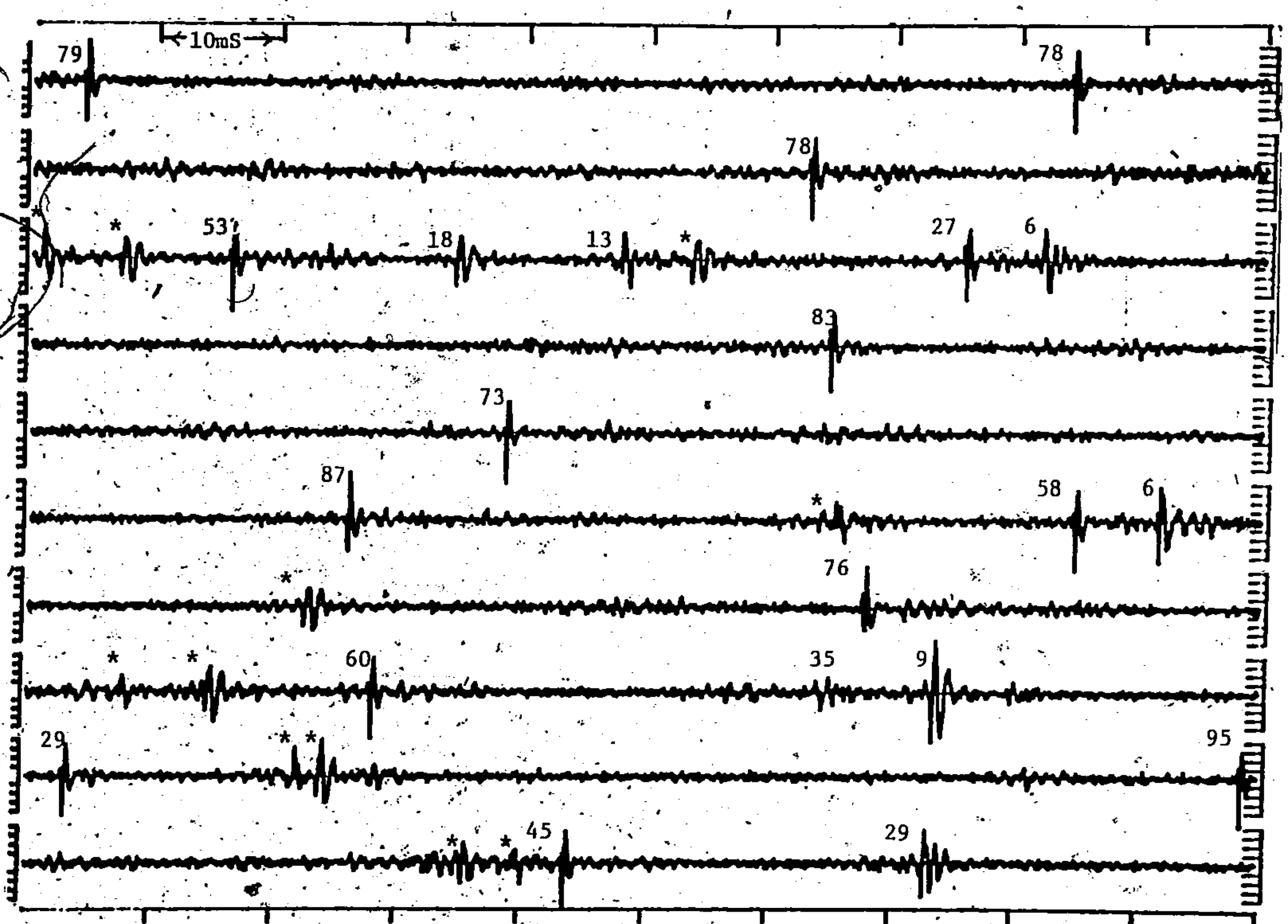


FIGURE 3.1
CONTINUOUS DATA

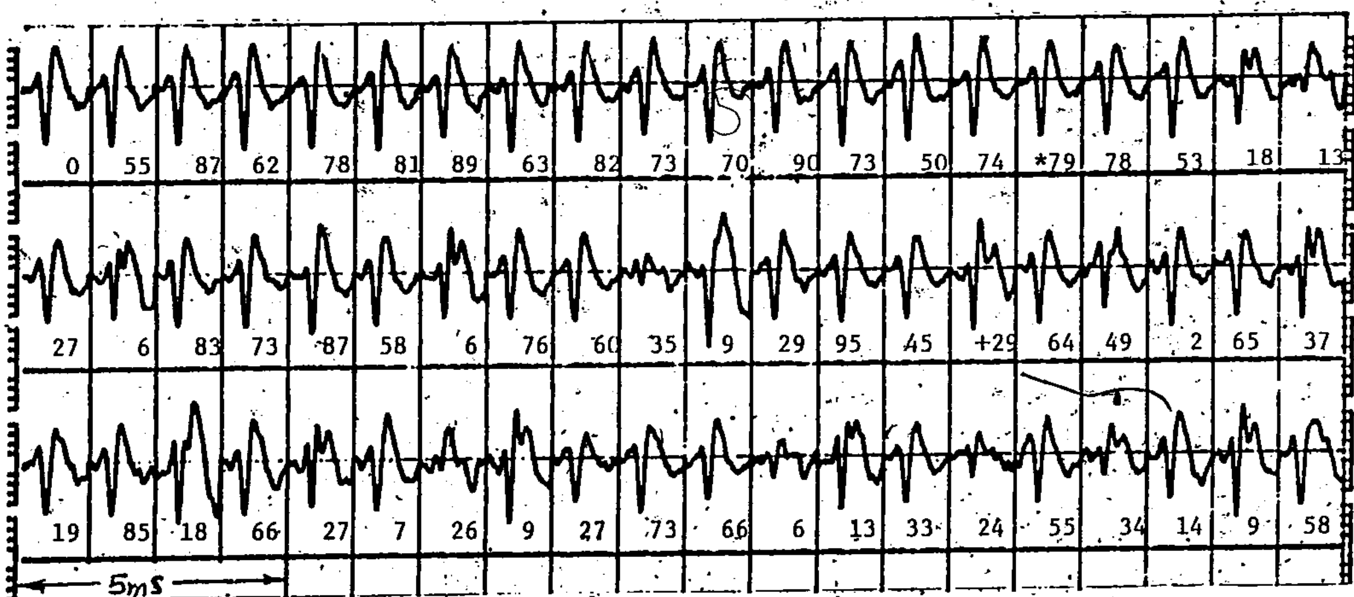


FIGURE 3.2
COMPRESSED DATA

milliseconds. With the high sampling rates used to represent MUAP shapes and the small proportion of the total signal needed to be saved, data compression reduces dramatically the storage requirements of the computer facilities used. The large number of MUAP's required to obtain valid results and the collection of a second channel of data further necessitates the use of data compression techniques.

The remainder of this chapter describes a new data collection-compression technique that collects and compresses two channels of digitized data, at differing sampling rates and stores the time of occurrence of each compression epoch. The structure of the data buffers and program interrupts used is outlined. The technique used to establish the occurrence of a suitable MUAP is explained. Data collection display routines are detailed. Expected error rates and possible problems with the technique are discussed. Finally, future uses of the technique with dedicated hardware are mentioned.

3.2 Collection-Compression Structure

The collection-compression algorithm is implemented on a PDP-11/34 computer using a LPS interface. The system can continuously digitize, sample and compress data from two channels. After initialization and at the start of the collection process, the program moves the data into a ring buffer. The occurrence of a MUAP then causes a section of the ring buffer, containing the desired MUAP to be transferred, to a compression buffer. The time of occurrence of the MUAP is stored in a timing buffer. This time is measured as the number of samples collected from the beginning of the collection, by an elapsed time counter. A schematic of the this structure can be seen in Figure 3.3. When the compression buffer is full, it is written to a compressed data file on disc via direct memory access (DMA). The collection-compression is continuous, but for these brief interruptions, until the timing buffer is full or the program is stopped by the operator. At this time, the current compression buffer contents are added to the compressed data file on disc and a separate file is written on disc, containing the timing buffer contents and information pertaining to the details of the collection-compression.

Program initialization is the process of quantifying program parameters, the calculations of necessary offsets or constants and the starting of counters or timers. Program termination routines stop any ongoing activity and store any remaining information needed. For the collection-compression program just outlined the initialization and termination is performed by a Fortran master program. Inputs are obtained under this Fortran master and later passed to an assembly language routine. Outputs are then passed from the assembly language routine to the Fortran master at the end of a collection-compression sequence.

The main parameters accepted by the Fortran program from the operator and passed to the assembly language program, either directly or in a further processed format, are: collection sampling rate, number of channels to be collected, number of samples to be compressed for each MUAP, ratio of collection and compression sampling rates for channel two, ratio of record to playback tape speeds and the minimum time

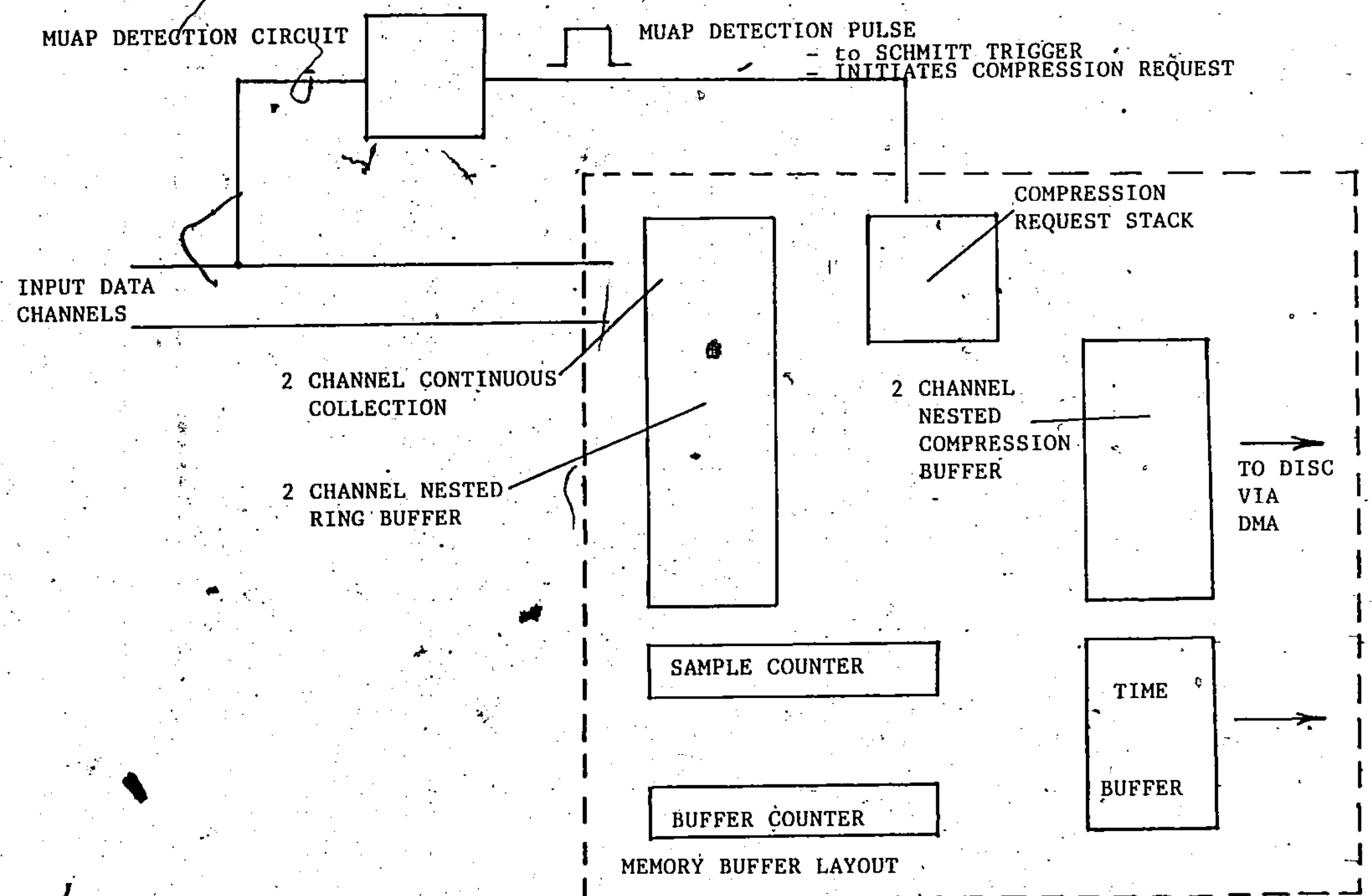


FIGURE 3.3

COLLECTION - COMPRESSION BLOCK DIAGRAM

between successive MUAP's allowed. The Fortran master defines the length of the ring, compression and timing buffers. It supplies their starting addresses to the assembly language routine along with the address of the DMA channel, the address of an elapsed time buffer used to time the DMA writing epochs and the maximum number of MUAP's that can be compressed. The maximum number of compressions that can be performed is dependent on the length of the timing buffer.

The assembly language program, based on the information passed to it from the Fortran master, then initializes the necessary offsets, increments, pointers, DMA parameters, interrupt service routine addresses, interrupt priorities and the LPS A/D conversion and clock hardware. The collection-compression process is then started by pressing the space bar of the computer terminal, which starts the LPS clock.

The collection-compression algorithm performs several simultaneous functions. Two channels of data are continuously sampled and placed in a ring buffer. When MUAP's are detected, appropriate data compression requests must be generated and the times of occurrence stored. MUAP's do not occur in periodic fashion in a composite EMG signal and several MUAP's may occur clustered in time. Therefore compression requests must be stacked and executed as time permits. This is accomplished by designing the algorithm in the following way.

The collection-compression algorithm consists of five program states. These program states are entered with the following priorities. The program first responds to a sampling interrupt. It acquires and transfers the new data samples to the ring buffer. The ring buffer pointer and ring buffer counter are updated accordingly. It then services any MUAP detection interrupts, by transferring the necessary information to the timing buffer and the compression request stack. The third priority state is the transfer of the appropriate section of the ring buffer to the compression buffer. This state is not entered if the compression request stack is empty. The fourth state is a wait state. This state is entered if no interrupts are being serviced and the compression request stack is empty. The program waits for the next sampling or compression request interrupt. The fifth state is the DMA write state. The program performs a DMA write of the compression buffer contents to the compression data file on disc when the compression buffer is full or when a collection-compression run is ended. The exact time taken to perform the DMA write, usually less than 300 ms for the 10 kilo-word compression buffer used, is added to the elapsed time counter. The calculation of the elapsed time is therefore continuous. This allows the firing rates, calculated later, to be temporally compared with continuous force collections. A more complete description can be found in Appendix 2.

The process is ended by a second press of the space bar or when the maximum number of MUAP's allowed has been compressed (timing buffer is full). The LPS clock is stopped. The existing contents of the compression buffer are then, via DMA, written to the compression data file, the number of MUAP's compressed and program control is passed to the Fortran master. The Fortran program then writes the timing buffer contents, the value of the parameters input by the operator, the number of MUAP compressed and some textual information about the subject and the just completed collection-compression run to a separate file on disc before terminating the program.

At the end of a collection-compression run, the nested compressed data from both channels is contained in a compressed data file on disc. The times of the occurrences of the compressed MUAP's, represented as a number of samples count, are contained in a separate file on disc. The value of the operator entered parameters, the total number of MUAP's compressed and textual information about the run is contained in the timing file on disc. The combination of the contents of these two files is sufficient to suitably analyze the recorded EMG data.

3.3 Detection of a MUAP

Successful data compression is dependent on the reliable detection of the occurrence of suitable MUAP's. The definition of a suitable MUAP is dependent on the ambient noise level and the size and frequency content of the MUAP's desired. The noise is the sum of ambient thermal electrical activity and electrode noise (instrumentation noise) and the biological activity recorded from distant motor units. The instrumentation noise can be characterized by its low amplitude and wide frequency content. MUAP's recorded from distant motor units become attenuated and are composed of low frequency components. Therefore, they are easily differentiated from MUAP's recorded close to the needle, which are relatively large in amplitude and composed of high frequency components. Thus, if the recorded signal is continuously monitored and the occurrence of such differences is flagged, suitable MUAP's can be detected.

One technique for MUAP detection uses continuous estimates of the autoregressive time series models of the noise and the present EMG signal (Wolf 1984). A MUAP is detected when significantly different models occur. Guiheneuc (1984) uses recursive horizon filters to constantly measure signal and noise variance. When their ratio becomes greater than a detection threshold, a MUAP is present. Both of these methods are very powerful and have the advantage of being independent of the noise level. The computation time and effort for their implementation is a serious drawback.

LeFever and De Luca (1982) used amplitude thresholds on high pass filtered data to detect MUAP's. Distant motor unit activity is attenuated by the filter. The amplitude threshold is then set suitably above the noise level by the operator. The actual MUAP detection was performed on the sampled data. The technique proposed here is an adaptation of this. Amplitude and slope criteria are applied to a parallel, analog SFEMG signal channel to define the occurrence of a MUAP. The slope requirement allows the distant slow wave action potentials to be ignored. The amplitude threshold can then be set closer to the instrumentation noise level. This allows small amplitude, high frequency MUAP's, of nearby units to be compressed. The use of a parallel analog signal channel to detect MUAP's, allows the compressed MUAP's to be of their original shape and frequency content. High pass filtering attenuates any [illegible] low frequency content the individual MUAP's might have, consequently making them more similar in shape.

Therefore, the unfiltered MUAP's will have better separation as defined in the subsequent classification process. Larger separation will improve the performance of the classification scheme.

The recorded signal is then simply electronically monitored for amplitude and slope. The monitoring is performed by the MUAP detection circuit. A full description of the MUAP detection circuit can be found in Appendix 1. A MUAP is detected when both amplitude and slope thresholds are exceeded within a set time. The amplitude threshold is adjustable. Typical values range from 0.2 mV to 0.4 mV. The slope threshold is also adjustable, with values in the range of 2 V/s to 6 V/s used. The time interval in which both these threshold must be met was set at 0.1 ms.

The detection of a MUAP results in a pulse output by the MUAP detection circuit. The pulse acts as an input to the computer and causes a compression request interrupt, which results in the correct compression of the MUAP, as recorded on both channels, as explained in the previous section.

3.4 Present Use and Validation

The collection-compression program and associated hardware just described was used to obtain efficient digital storage of the data recorded, using the protocol introduced in Chapter 2. This section reports on the specific collection-compression parameter values used for this data storage. It deals with the assessment of the consistency and accuracy of the stored data. The results of these tests are included along with possible problems with the technique. The section concludes with a discussion on the limitations of the present implementation and potential future uses of the technique.

The high frequency content of the SFEMG MUAP and the band pass filtering used with the collection protocol, necessitates a minimum 10 KHz sampling rate for this data channel. Due to the way some pattern recognition schemes use the data, much higher sampling rates may be required. However, the method used to represent the MUAP's in the pattern recognition algorithm proposed later, allows the minimum Nyquist sampling rate to be used. This will be further discussed in Chapter 4. The sampling frequency requirement for the cannula data is much lower. Therefore, the required rate for the SFEMG data determines the required collection sampling rate for both channels. A 10 KHz collection sampling rate was used.

As just mentioned, the macro MUP's do not require the same sampling rate as the SFEMG MUAP's. This allows the use of a lower compression sampling rate for the cannula data. Only every fourth collected data point for channel two was compressed. This resulted in a 2.5 KHz effective sampling rate for the cannula data.

Due to the long durations of macro MUP's, 50 samples were compressed for each MUAP detection. This, combined with the reduced compression sampling rate, resulted in a 20 ms time representation for each macro MUP extracted. This is a shorter time than used by Stalberg (1983). Consequences of this will be discussed in Chapter 5. The 50 samples compressed for each SFEMG MUAP resulted in a 5 ms duration being stored. This duration is longer than required for most SFEMG MUAP's and is dealt with in the next chapter. The SFEMG data is monitored for the occurrence of an MUAP, as described in the previous section. The minimum time between successive MUAP's was set at 1 ms which is the typical SFEMG MUAP duration.

The ring buffer is written over when full, starting at the beginning. The ring buffer must therefore be long enough or the real time sampling rate low enough that all the necessary compression transfers are completed before the original data is written over. Due to memory limitations, a 5 kilo-word ring buffer was used for this implementation. This limits the real time sampling rates that can be used when the frequency of compression requests is high. This resulted in the need to use a 2.5 KHz real time collection sampling rate and a tape playback speed four times slower than the tape record speed when the recorded data was collected and compressed. An effective 10 KHz collection sampling rate was obtained, but not in real time.

The accuracy of the collection-compression routine was determined by visually comparing the MUAP's compressed with the continuously collected signal. The number of missed MUAP's and the number of false compressions were used to assess the system accuracy. The slope and amplitude criteria used to define the occurrence of a suitable MUAP greatly affected the results. A 4 V/s slope criteria and a .2 mV amplitude threshold was found most successful for the range of recorded signals tested. The comparisons revealed that for these slope and amplitude thresholds, the desired MUAP's are successfully compressed approximately 99% of the time, MUAP's from distant units with low slope or amplitude are not compressed and the number of false compressions is very low. The MUAP's that are missed are usually the result of rare superpositions which reduce slope or amplitude, the minimum interval between MUAP not being met or minor intermittent shape changes due to slight needle movement.

The consistency of the technique was tested by collecting-compressing the same segment of recorded data several times using the same slope and amplitude criteria. Changes in the MUAP's compressed with each run were then determined. Studies of this nature showed the technique to be 100% consistent as far as the specific MUAP's compressed from run to run. However, alignment differences within a run, as to the actual triggering point in the MUAP's, were observed. This can result in MUAP's recorded from the same motor unit having phase differences. Varying triggering points of similarly shaped MUAP's from the same motor unit can occur due to random noise, but do not occur often. Consequences of this effect will be discussed in the next chapter.

The present implementation of this technique results in some limitation, which could be overcome with different hardware. Typically, a 20 KHz sampling rate for two data channels is obtainable. Collecting at this rate, however, would quickly fill up the ring buffer. The time between samples available to perform data compression would also be reduced. The ring buffer would be written over and the compressed data contaminated. If a larger memory were available, a larger ring buffer could be used. This would then allow sufficient time for the necessary data compressions to be successfully performed, even at higher sampling rates. Real time data collection-compression would be possible and the intermediate step of recording the data on tape could be avoided. Increased memory would also allow more compression to be performed continuously due to the use of a larger compression buffer. A larger total number of MUAP could also be compressed if the timing buffer size could be increased.

The program and the associated electronic monitoring device were developed with a specific goal in mind. This goal was the efficient storage of the data required for the new protocol introduced in Chapter 2. The developed system can, however, be used for the storage of data resulting from any source that can be conceptualized as having a structure similar to the data of the application reported here. The hardware changes proposed would allow the system to become a more general collection-compression technique. It would allow for the real time collection-compression of data from many similarly structured sources.

3.5 Data Display Routines

The collection-compression routine described in the previous sections stores the samples representing the MUAP's, as recorded on the two data channels in nested format in an unformatted compressed data file on disc. The times of occurrence of the MUAP, represented as the number of full ring buffers collected, and the number of samples collected in the current ring buffer are placed in an unformatted timing data file. The values of the collection-compression parameters input by the operator during program initialization, the total number of MUAP's compressed and some textual information is also included in the timing data file. A program was written to display this data on the screen of a Tektronix 4006-1 display terminal and 4631 hardcopy unit. This section reviews the capabilities of this program.

The data can be displayed one channel at a time or both channels can be displayed together. The MUAP's are plotted from left to right as potential versus time. Consecutively compressed MUAP's are plotted in a continuous row from left to right. Amplitude scales, in millivolts, at each end of the display indicate the recorded size of the MUAP's. The scale multiplier used is adjustable after viewing the first row of the display. This allows the display to be adjusted to optimally fill the available space. Continuous vertical lines demarcate the compression epochs and numbers indicate the elapsed time in milliseconds between the consecutively compressed MUAP's. The rows are continuous from right edge to left edge for single channel displays, and are likewise continuous in pairs for two channel displays.

The display is headed with textual information about the collection-compression. This information includes: the file name, total number of MUAP's compressed, multipliers for the MUAP amplitude scales, number of pages required to display all compressed MUAP's, the current page number, number of channels compressed, channel numbers displayed, number of samples compressed per MUAP, number of samples displayed per MUAP, collection to compression sampling rate ratio for channel two data, effective sampling rate for channel one, total collection time, MUAP detection slope and amplitude criteria and the minimum time allowed between consecutively compressed MUAP. Inclusion of these parameters is necessary to efficiently document the data collection.

The number of samples displayed per MUAP can be less than the number compressed. This allows for a variable time resolution and duration in the display. The operator can choose between 25, 50 or 100 samples to be displayed. The number of samples chosen for display must be less than or equal, to the number compressed. The number of samples displayed must be the same for both channels when two channels are displayed together. The samples displayed for each compression epoch are always centered on the time of its corresponding compression request interrupt. The data can also be displayed differenced. This means that the value of the difference between adjacent MUAP data samples is used to represent the MUAP potential.

The display for a single channel consists of 10 rows of 20 MUAP's each for a total of 200 MUAP's displayed at one time. The first 200 MUAP's are initially displayed. Successive displays of the remaining MUAP's can then follow. The time between each MUAP is included in the display next to each MUAP. An example single channel display is shown in Figure 3.4. This figure shows 200 MUAP's collected with the selective needle surface of the recording needle electrode. An effective 10 KHz sampling rate was used for this compression and 25 samples per MUAP are displayed. Therefore, each compression epoch has a 2.5 ms duration. Either channel can be singly displayed in this manner.

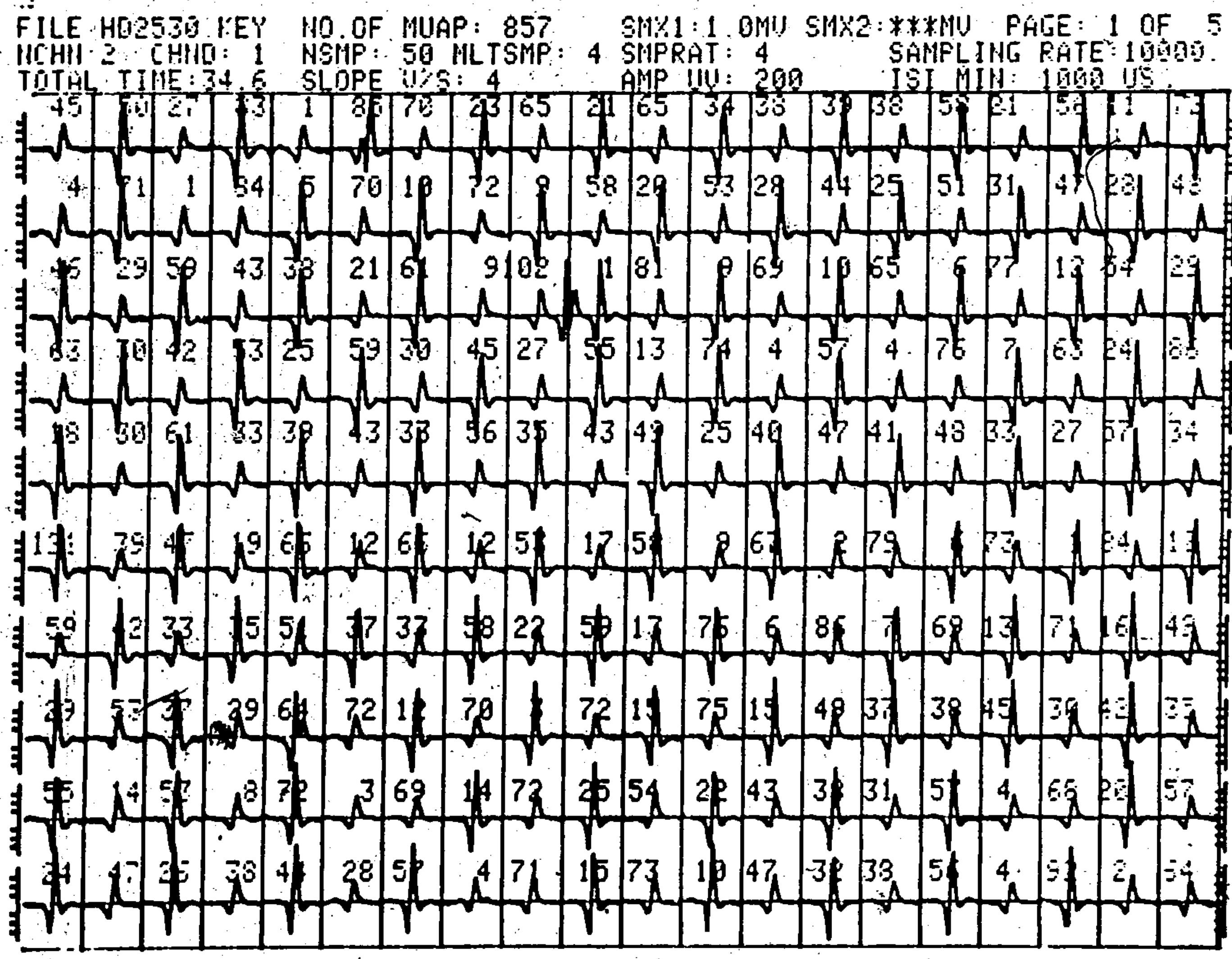


FIGURE 3.4
COMPRESSED DATA ONE CHANNEL DISPLAY

Displays which include data from both recorded channels plot the respective MUAP's in alternating rows. One row displays the data from channel one. The next row displays the concurrent second channel data. This alternation of the data displayed continues through to the tenth row. The two representations of the same MUAP therefore appear next to each other vertically, with the channel one representation on top. The total number of MUAP's displayed at once is 100. The times between the MUAP are displayed next to a channel one MUAP representation, then a second channel MUAP representation alternately across the row pairs. Figure 3.5 is an example display of both channels together. The data is the same as is displayed in Figure 3.4 with the addition of the cannula response. The effective sampling rate for the selective needle recording is again 10 KHz. A collection to compression sampling rate ratio of 4 was used for the second channel. Therefore, the effective sampling rate for the second channel is 2.5 KHz. The number of samples displayed per MUAP is 50. Therefore the compression epoch is 5 ms for channel one and 20 ms for channel two. The use of the data display routine in the analysis of the recorded data is discussed in later chapters.

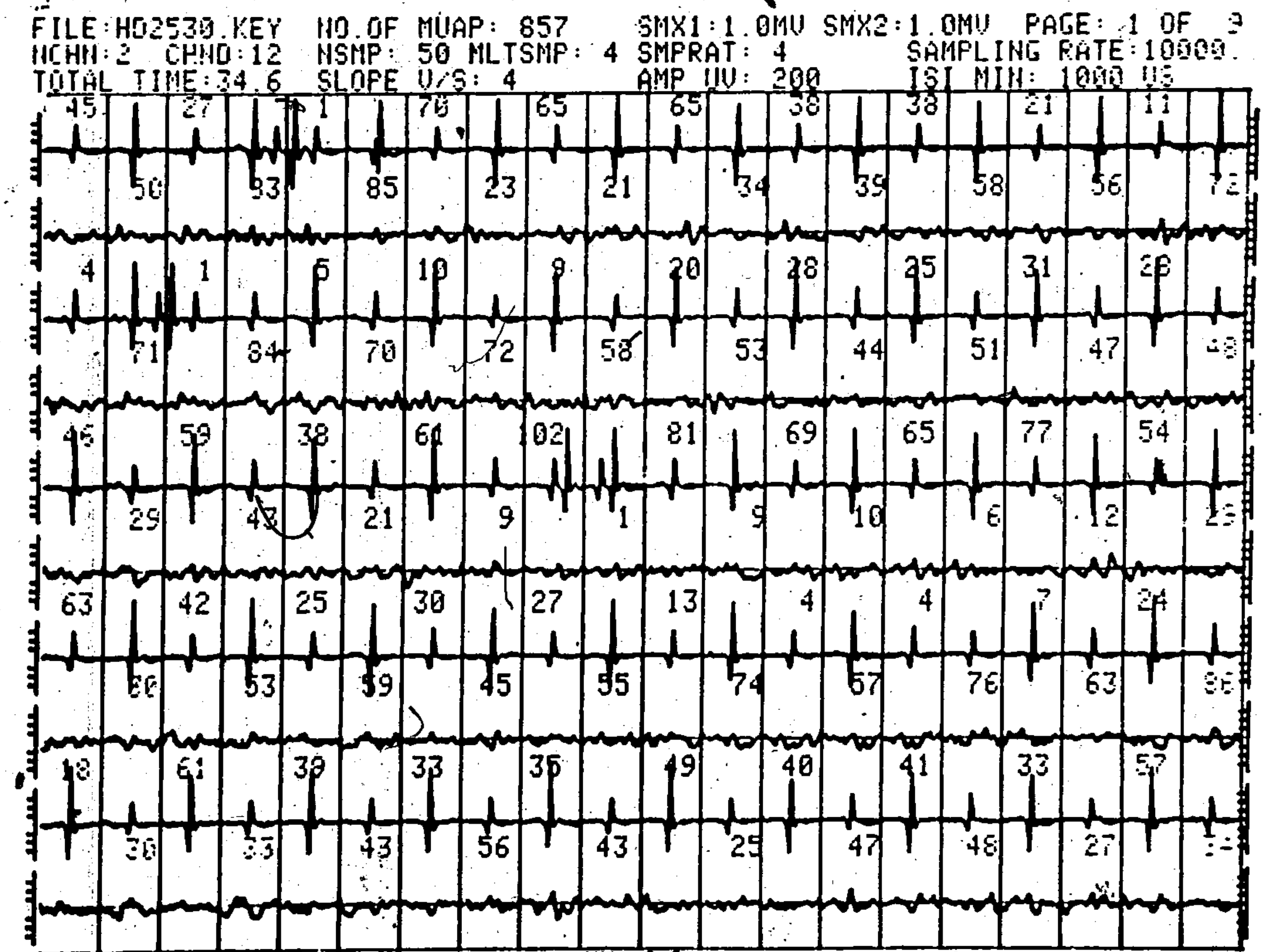


FIGURE 3.5
COMPRESSED DATA TWO CHANNEL DISPLAY

CHAPTER 4

PATTERN RECOGNITION AND SIGNAL DECOMPOSITION

4.1 Introduction

The extraction of individual motor unit rate coding information and the calculation of a macro motor unit potential (MUP), for each motor unit of a population of concurrently active motor units, requires the decomposition of the composite EMG signal, into its component motor unit action potential trains (MUAPT's). The decomposition of an EMG signal requires the recognition of the individual motor unit contributions to the composite signal. Recognition of these individual contributions involves the differentiation of the shapes and firing patterns of the individual motor unit action potentials (MUAP's) present in the composite signal. The classification of each individual MUAP, as belonging to a specific MUAPT, is effected by pattern recognition methods.

This chapter outlines the concepts of pattern recognition as they are applied to the decomposition of the EMG signal. The pattern representations, class definitions and comparison methods utilized are introduced. The signal and feature space representations adopted are explained. Shape templates and similarity measures are defined. Various distance measures considered for the evaluation of the similarities of two shapes are reported. The value of additional information, contained in the firing patterns of the motor units, to the classification process is discussed.

The chapter concludes with a full description of an algorithm developed to decompose the composite SFEMG signals stored with the collection-compression routine outlined in Chapter 3. Template initialization and updating methods are detailed. The order in which the compressed MUAP's are classified is presented. The assignment criteria and timing constraints used for the classifications are defined. The handling of superpositions of MUAP's is explained and the format for the presentation of the decomposed data is described.

4.2 Pattern Recognition

4.2.1 Pattern Recognition Concepts

Humans perform pattern recognition of sensory events by the following perceptual process. The event is first sensed, the sensory inputs are then analyzed and finally classified or recognized as being familiar to previous sensory experiences or not. The event may be of any sense (hearing, visual, taste, etc.) or a combination of several. More abstractly, the event may refer to conceptual or logical thought processes.

For pattern recognition to be performed automatically or by machine, the data must also be handled in a methodical way as with the human experience. The event must first be measured and the measurements must be stored by the machine. The stored measurements must then be analyzed and compared to defining prototypes stored in memory. Recognition or classification is then dependent on this comparison. As with human pattern recognition, the events may be stored in many different data forms and may be quite abstract in nature.

The goal of automatic pattern recognition is to provide a machine with a perceptual capability so that it can be used to automate the analysis and extraction of useful information from data. Figure 4.1 shows the parallel between human and machine pattern recognition schemes. In each case, memory affects the sensing (measurement), analysis and recognition of the patterns. Following, is a discussion of the pattern recognition concepts used for the automatic decomposition of the EMG signal. A more general and detailed account of pattern recognition techniques can be found in Duda and Hart (1973).

Pattern recognition, as pertaining to the decomposition of EMG signals, is the attempt to automatically determine, for a particular event, which of a number of classes of events, if any, it is a member. Belonging to or generated by a specific class means that the event has similar properties as other events in its class. It also means that the event has properties which are different from properties of the events belonging to the other existing classes. The classes of events must be suitably separable or have different properties for pattern recognition to be possible.

The properties of an event which determine membership to a certain class are defined as features. The features of the event being classified must then be quantified and compared to the features of the prototype event for each existing class. The features of the representative event of a particular class create a template for that class. An event is assigned or recognized as belonging to the class

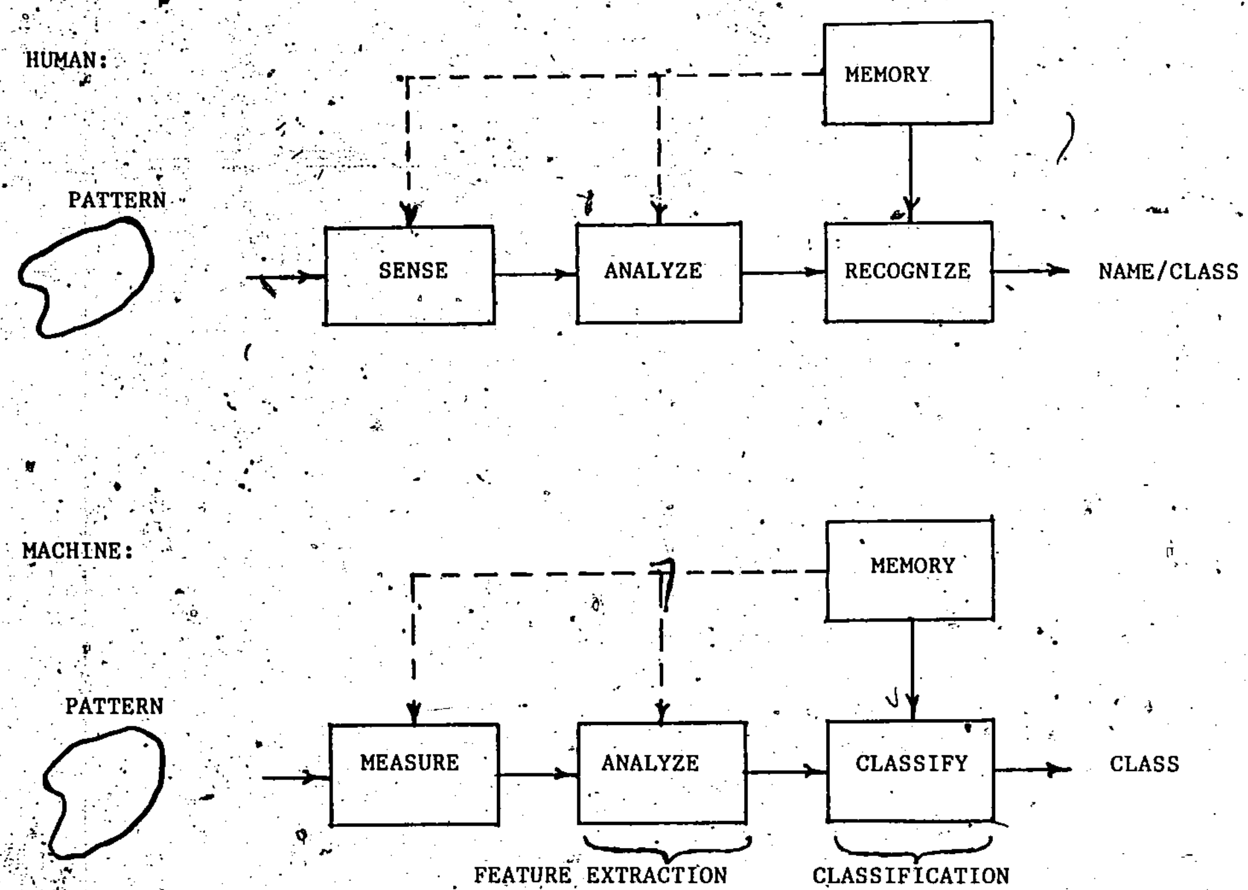


FIGURE 4.1

PATTERN RECOGNITION CONCEPTS HUMAN-MACHINE whose template is most similar to the features of the event being classified.

The quantification of the similarity between class templates and event features is called a distance measure. The definition of distance measures are dependent on the way in which the events are represented. Usually, as distance measures increase, the similarity between the compared events decreases.

The number of classes and their definition must be determined. If this is determined automatically and adaptively by the pattern recognition algorithm the process is termed unsupervised classification. Clustering techniques such as PFS clustering, introduced by Vogel and Wong (1979), are examples of unsupervised classification. Alternatively, if the number of classes and their initial templates are determined before the pattern recognition algorithm starts or are input to the algorithm, the process is called supervised classification.

The events to be classified in this application are the individual MUAP's compressed from the SFEMG channel as described in Chapter 3. The MUAP's are represented by their compressed samples and times of occurrence. The N samples compressed, can be considered as elements x_i of a N dimensional vector X, where

$$X(i) = x_i \qquad i = 1,N \tag{4.1}$$

Each of the compressed samples then represents a single dimension in the N dimensional space. This geometric conceptualization of the compressed data is called the signal space representation.

Each vector of compressed data samples represents the shape of the MUAP's. Shape-comparisons between MUAP's is the prime basis of the classification scheme developed in this work. The time of occurrence also contains useful information. The nature of this information and its use in the classification process will be explained in section 4.3.

The quantification of the comparison of the shapes of MUAP's requires the definition of distance measures. A distance measure is a mathematical equation which is intended to measure the similarity or difference of two shapes. Distance measures are based on the differences or similarities of features of the compared shapes. A feature is an element or property of a shape which aids in the shape's differentiation from other shapes. A feature can simply be a specific data point in the signal space or it can be the result of a calculation based on all or some subset of the data points in the signal space.

The selected features of a shape create a feature space of equal or less dimensionality than the signal space. The signal space representation is then mapped or transformed into the feature space when the features are calculated or selected. The number of features extracted from the signal space representation is generally less than the dimensionality of the signal space. This reduction in dimensionality reduces the time required for distance measure calculations. The features used to represent the MUAP's for template initialization and distance measurements are determined based on the desire for minimum feature space dimensionality and maximum separation of the MUAP projections into this space.

Dinning and Sanders (1981) proposed a method of selecting features for the real time unsupervised classification of biological action potential (AP) shapes. The resulting features are data samples chosen from the AP sample sequence which best differentiate it from other AP shapes. The samples are chosen on the basis of maximum separation between classes for a specific data sample and a minimum variance of the values of this data sample. The technique uses the complete set of unclassified collected data as a learning set to determine the optimum number of features to be used and the specific samples to be used as features. The process is completely automatic but less successful for data sets with more than two classes present.

Bak and Schmidt (1977) used AP amplitudes at unique points during their time course as a single feature to select specific shaped AP's from multi-unit data. The process was performed using special hardware and an oscilloscope display. The shapes were selected by placing an amplitude window at specific points during the AP's occurrence which best differentiated it from the other AP's present in the data record. The window size and location was determined by viewing the oscilloscope display. The technique was successful, but required much operator time and input. Separate runs, with different window sizes and locations, had to be performed to extract each differently shaped AP.

Zalud et al (1976) selected four features of the AP shapes to differentiate neuronal spike data in real time. The selected features were functions of the AP shapes. The selected features were peak positive amplitude, peak negative spike wave value, time interval between consecutive crossing of two preset levels and the sequence of positive and negative components of the AP shape. The success of this approach was not reported.

Abeles and Goldstein (1977) proposed the use of principle component analysis to provide an orthonormal set of basis functions which are used to represent the sampled shapes of AP's. The basis functions are created from a learning set of representative AP shapes. The requirement of a learning set of representative AP shapes makes such an analysis unlikely for the EMG decomposition problem. The learning sets would become too large because of the large number of possible MUAP shapes and the required accuracy of the resulting representations.

A variation of principle component analysis, also using a learning set was proposed by Nandekar and Sanders (1984) for the efficient representation of MUAP's. The MUAP's so represented would then later be classified as normal or pathologic based on their computed features. Nandekar et al (1984) reported on similar work using macro MUP's and Hermite polynomials. Learning sets are feasible for these applications because of the lower accuracy of the resulting representations needed. The lower accuracy is sufficient because only normal versus abnormal responses are differentiated.

The features chosen to define the shapes of the MUAP's can affect the sampling rates that are needed for the initial signal representation and the required dimensionality of the signal space. If the data samples are directly used as features for the construction of templates, the required sampling rate may be as high as seven times the minimum required Nyquist rate (McGill and Dorfman 1984). This is to reduce resolution errors in the shape definition of the MUAP's to acceptable levels (Lefever and De Luca 1982). Alternatively, if the compressed data samples are Fourier transformed and the resulting Fourier coefficients are used as features to represent the MUAP shapes, the sampling rate can be the minimum required Nyquist rate (Bendat and Piersol 1971).

The Fourier representation is one using orthonormal basis functions and is, therefore, optimum in the mean square sense (Nandekar and Sanders 1984, Abeles and Goldstein 1977). The MUAP's are then transformed into the frequency domain. The dimensionality of the feature space is equal to that of the signal space in this case. The required dimensionality of the signal space is, however, greatly reduced.

A further reduction in the dimensionality of the feature space can be achieved if the MUAP's are represented by the value of their frequency domain power spectrum coefficients. The number of features required is then reduced by half as compared to the number of frequency domain coefficients. A further reduction of one is accomplished when the DC coefficient is set to zero by removing the mean.

This feature selection results in a representation which contains no phase information. The phase information is lost with the calculation of the power spectral coefficients. The consequences of this are both beneficial and detrimental. In the time domain or in the frequency domain when phase information is used to help differentiate between MUAP shapes, alignment is necessary to find the minimum distance or optimum match between shapes. Alignment of MUAP templates is not necessary when phase information is not used. This allows the comparison of MUAP shapes with the minimum of computational effort. However, if the difference in two compared MUAP shapes lies primarily in their phase differences, the lack of this phase information will make their successful differentiation less likely. The net effect of these consequences on distance measures and successful MUAP classification will be discussed later in this section.

The resulting dimensionality reduction that can be obtained by using the power spectral coefficients as features for the MUAP representations as compared to the use of the time samples, is by a factor of greater than eight. The dimensionality reduction is primarily due to the ability to sample at the Nyquist rate. The reduced number of features together with the ability to calculate distance measures without alignment of the MUAP's, greatly reduces the required time for distance measure calculations. This will be explained more fully later in this section. The time saved during distance calculations outweighs the time required for the calculation of the power spectral coefficients. This makes the use of the power spectra coefficients of the MUAP's as features for all distance measurements an inviting approach.

4.2.2 Feature Space Selection

Initial pattern recognition attempts, using the time domain samples of the MUAP's as features for distance calculations, were extremely slow due to the computational encumbrances of large feature space dimensionality and the need for template alignments. These attempts, combined with the discussions of the previous section, led to the use of the power spectral coefficients of the MUAP's as features for distance measure calculations.

The compressed SFEMG MUAP shapes, as defined by the compressed samples contained in the data files created during collection-compression, as described in Chapter 3, are considered as elements x_{ji} of vectors X_j, where;

$$X_j(i) = x_{ji} \qquad i = 1,N \qquad j = 1,L \tag{4.2}$$

N is the number of samples compressed per MUAP

L is the number of MUAP's compressed

The time domain vectors $X(i)$ are Fourier transformed into the frequency domain vectors $F(k)$ by the following equation.

$$F_j(k) = \sum_{i=0}^{N-1} X_j(i) * e^{-j2\pi ik/N} \qquad k = 0,N-1 \quad j = 1,L \tag{4.3}$$

where. $e^{-j2\ \ k/N}$ is a complex sinusoid

$F(k)$ is the kth complex frequency coefficient of the jth MUAP.

The vectors $P(m)$, containing the power spectrum coefficients of the SFEMG MUAP, are obtained from the corresponding frequency coefficient vectors $F(k)$ by the following equation;

$$P(m) = 2 * |F(m)|^2 \qquad m = 1,(N-1)/2 \tag{4.4}$$

where $P(m)$ is the mth power spectrum coefficient

The absence of a DC power spectral coefficient, and more details of these transformations and calculations will be presented in section 4.4. The power spectrum coefficients, contained in the P (m) vectors, are then used as features to represent the MUAP shapes in the EMG decomposition algorithm. Figure 4.2 illustrates the representation of some typical MUAP's in the time and power spectrum domains.

4.2.3 Distance Measures

The features chosen to represent the shape to be classified are placed in a m dimensional vector, X, where m is the number of features chosen. The features of the representative shape or template for a specific class are also placed in a m dimensional vector, T. Distance measures are usually based on the sum of the squared difference of all of the corresponding elements of the feature vectors being compared. The difference is squared to ensure it is positive and to reflect the power or energy in the difference. Both feature vectors are usually normalized to sum to one to remove any scale bias in the compared shapes. The following equation reflects the typical distance measure.

$$D = \sum_{i=1}^{m} (X(i) - T(i))^2 \qquad 4.5$$

where X(i) is the ith element of the m dimensional feature vector

T(i) is the ith element of the m dimensional template vector

both X and T are normalized such that:

$$\sum_{i=1}^{m} T(i) = 1 \quad \text{and} \quad \sum_{i=1}^{m} X(i) = 1$$

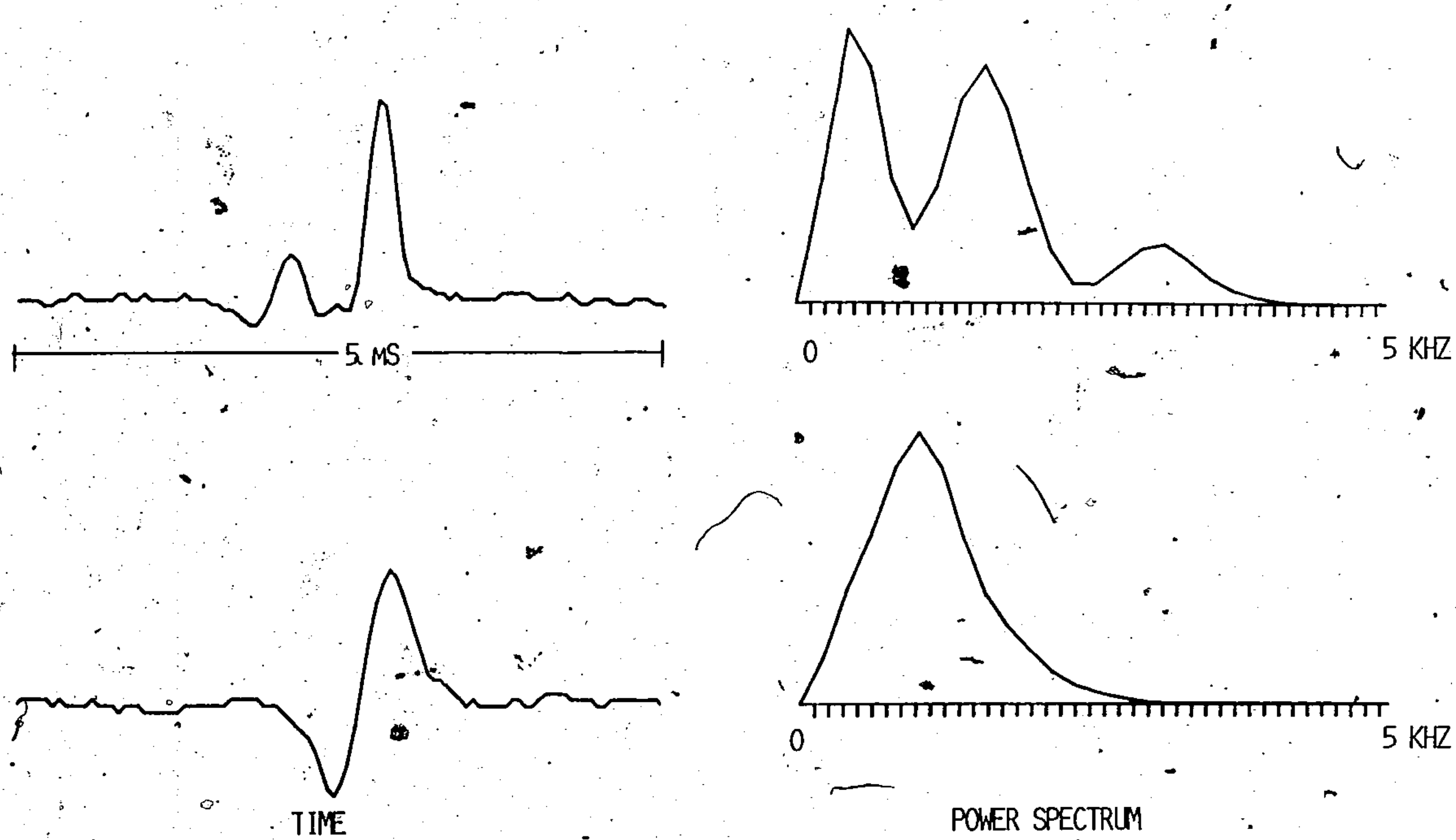


FIGURE 4.2

TIME AND POWER SPECTRUM DOMAIN MUAP REPRESENTATIONS

A shape is generally assigned to the class whose template results in the smallest distance measure when compared to the shape in question. This means that the shape is classified as belonging to the class with the most similar template.

The representation of the MUAP's by their power spectral coefficients already exists in an energy or power domain. Therefore, the sum of the absolute value of the difference of corresponding elements of the feature vectors is an appropriate variation to the standard distance measure. The amplitude of the recorded MUAP's is an important feature for their differentiation. Therefore, the feature vectors are not normalized, but are left as originally calculated. The resulting modified distance measure becomes:

$$D = \sum_{i=1}^{m} \left| (X(i) - T(i)) \right| \qquad 4.6$$

where $X(i)$ is the ith element of the m dimensional feature vector

$T(i)$ is the ith element of the m dimensional template vector

both X and T are not normalized

The values of the distance measures obtained were compared with subjective estimates of the similarity of the MUAP shapes. These estimates were determined visually in the time domain using the display programs described in section 3.5. These correlations were performed to determine the effects of lost phase information and to check the appropriateness of the altered distance measures.

This analysis of the results of the distance measures revealed that the lack of phase information was generally of little consequence. Occasionally, the outcome of the distance measure would not reflect the actual situation as seen in the time domain, but these occurrences were rare.

These visual comparisons also showed that the distance measure used should take into account the amplitude of the template, from which distances are being measured. Distances calculated from large templates may result in large distance measures, compared to distances measured to smaller templates, strictly because of the template amplitude and might not reflect the true similarity of the compared shapes. Therefore, a bias towards the classification of shapes to classes with small templates exists.

To avoid this situation, the distance measure can be normalized by the size of the template. Therefore, the resulting distance measure becomes a percentage of the template size. Classification of a shape is then, to the class which has the most similar template, proportionally measured, based on each class' template size. A shape may be further from a large template of one class than a smaller template of another class, as measured by Equation 4.5, but still be assigned to the class with the larger template, if the total measured difference from the larger template, proportional to the larger template's size is minimum. This is a reasonable assignment criteria because the total variations in the recorded shapes, from a single motor unit, are seen to be greater with larger MUAP's. A change in the variability of MUAP shapes with size was also reported by LeFever and De Luca (1982).

The larger variations may be caused by an increased sensitivity of the larger recorded MUAP to needle movement. This increased sensitivity may exist because of the exponential decay of recorded potential sizes with distance from a muscle fibre and the close proximity of the needle to the muscle fibres creating the large MUAP's. Another reason larger MUAP's are more variable may be due to a possible larger number of contributing fibres. The recorded MUAP's may, therefore, be subject to larger amounts of neural transmission and conduction velocity variations, which can cause changes in the recorded shape.

The normalization of the distance measures to the template size can take various forms. The equations below describe two that were studied.

$$D = \sum_{i=1}^{m} \left| (X(i) - T(i)) \right| \Big/ \sum_{i=1}^{m} T(i) \qquad 4.7$$

where $X(i)$ is the ith element of the m dimensional feature vector

$T(i)$ is the ith element of the m dimensional template vector

both X and T ~~are~~ not normalized

The normalization factor is the power in the template vector. The comparison of the results of this distance measure with distances assessed visually in the time domain, revealed that this distance measure contains a bias. The bias is that shapes are more likely to be assigned to classes which had large templates. The normalization factor is too great. It overcompensates for the template size. The following adjustment was tried.

$$D = \sum_{i=1}^{m} \left| (X(i) - T(i)) \right| / \sqrt{\sum_{i=1}^{m} T(i)} \qquad 4.8$$

where X(i) is the ith element of the m dimensional feature vector

T(i) is the ith element of the m dimensional template vector

both X and T are not normalized

The normalization factor is the square root of the power in the template vector. This resulted in a distance measure which, based on visual comparisons of the time domain shapes, appears not to be biased to either large or small templates. This distance measure was used in the developed decomposition algorithm to be described in section 4.4.

The distance measures defined above assume the template and the shape being classified are aligned with each other. Any relative shift will result in a higher than minimum distance measure. Therefore, the shape being compared must be aligned with the template to ensure the minimum distance measure result. Such alignment can be a time consuming process. The time required to calculate the value of the distance measures defined above increases with the dimension of the feature vectors. As the dimensionality of the feature space, m, increases, it can be seen that the time required to calculate a result for equations 4.5 to 4.8 increases.

Using power spectrum coefficients as features, therefore has the advantage of greatly reducing the time required for calculating distance measures. The disadvantages, of this representation are the time required to calculate the features and a reduction in the separation of some MUAP shapes due to the lack of phase information. The net effect of power spectrum coefficient representation is judged beneficial.

The number of motor units firing and the representative shape of the MUAP's of each motor unit (template for each class), must be initially determined for pattern recognition to begin. The methods used to initialize the templates and for the updating of the templates will be discussed in section 4.4. The firing patterns of each motor unit should also be helpful in the classification process. This factor and how it is used in the decomposition algorithm is discussed in the next section.

4.3 Motor Unit Firing Model

Throughout a muscle contraction, motor units fire on a regular basis. The times between firings or interpulse intervals (IPI's) of a specific motor unit are in no way deterministic, but they can be modelled as a random variable (RV) of a stochastic process. A stochastic process is defined in a probabilistic sense. This means that the likelihood of the occurrence of an event during a certain time period or the occurrence of a RV having a value in a certain range of values is dependent on a probability distribution. The probability distribution of a RV is defined by a given probability density function (PDF). The PDF is usually a completely defined mathematical function but for two parameters, location and scale. The probability distribution of the RV is centered on the mean or location parameter. The distribution of the values of the RV about the mean is dependent on the variance or scale parameter. For a more complete description of random variables and stochastic processes, see Papoulis (1965).

The firing of a motor unit has been modelled as a gaussian renewal process (Clamann 1969). This means that the IPI's can then be modelled as having a certain mean value and a gaussian distribution of values, with a certain variance, about this mean. It also means that the time intervals between subsequent firings of the motof unit are independent of each other. The firing intervals of a motor unit are not stationary, however. The nonstationarity of the mean IPI value has been determined to be a function of force and the length of time the motor unit has been active (De Luca and Forrest 1973). The variance of the IPI's is also nonstationary. It was found to be a function of the mean IPI value (Clamann 1969, Person and Kudina 1972). Assuming the gaussian model the probability distribution of the IPI's of a specific motor unit can be completely determined by knowing its mean and variance. Estimates of the mean and variance must, however, be constantly calculated because of the existing nonstationarities.

The assumed probability distribution of the IPI's allows for the determination of the expected firing times of the individual motor units, given the last time of firing. It also allows for the determination of time limits, based on calculated IPI's, beyond and before which, the firing of a specific motor unit is very unlikely. These IPI limits can be used in determining if a MUAP being classified, was likely created by a certain motor unit, from an IPI standpoint.

If a MUAP is classified as being created by a specific motor unit based on distance measures, but this classification results in an IPI, which for that motor unit is highly unlikely, based on the probability distribution of the IPI's for that motor unit, the distance measure based classification becomes questionable.

IPI limits defining a range of IPI values, beyond which an IPI value is very unlikely, can be determined for each motor unit. The IPI limits are calculated based on the current estimates of the mean and variance of the IPI PDF of each motor unit. The IPI's calculated for each classification can then be compared to the IPI limits for that motor unit as a check to determine if the assignment of the MUAP to this motor unit is appropriate. The IPI limits for each motor unit can be set to flag any assignment which creates an unlikely IPI, one which falls in a range of IPI values which has a probability of a predetermined low value.

The course of action taken once a classification is flagged can then be determined by the probability of the IPI value which created the flag and the distance measures leading to the particular classification. The use of this information in the decomposition algorithm is described in section 4.4.

4.4 Signal Decomposition Algorithm

4.4.1 Introduction

Following, is a description of a computer algorithm to decompose a SFEMG signal recorded, according to the protocol laid out in Chapter

2. The SFEMG signal is sampled, collected and compressed by the technique outlined in Chapter 3. The compressed samples of the MUAP's exist in a file on disc created by the collection-compression program. The algorithm is written in Fortran and implemented on a PDP-11/34 computer.

The decomposition of the EMG signal is effected by a supervised pattern recognition scheme. Each of the compressed MUAP's is classified as belonging to or being created by a certain motor unit or, as noise or a spurious compression. The classification is primarily based on distance measures to the representative MUAP templates for each motor unit. However, if a classification based on the distance measures creates an unlikely IPI value for a motor unit, the classification is altered. If none of the motor units being considered could have likely produced a MUAP being classified, based on IPI values, it is assumed to be noise or a spurious compression. Details of this classification procedure will be given later in this section.

All of the MUAP's compressed are first visually assessed for stationarity using the data display routine described in section 3.5. This is accomplished by viewing the MUAP shapes at different points throughout the contraction and determining if the needle moved significantly, by checking the consistency of the recorded MUAP shapes. If the shapes change drastically with time the data must be rejected. This check is performed as a backup for the needle movement constraints used during data collection. If the data is found suitably stationary, the MUAP features are then extracted.

As mentioned in section 4.2., the MUAP's are represented by their power spectrum coefficients for all distance measures. The transformation from the signal space to the feature space is performed by a separate program. This program takes the middle 32 of the 50 compressed samples and calculates their Fourier transform. The data points are initially Hamming windowed to reduce frequency spreading due to discontinuities at the data vector ends (Bergland 1969). The resulting samples are then Fourier transformed, by a decimation in time FFT algorithm (Brigham 1974). The power spectrum coefficients are then computed based on the theory of periodograms as applied by Welch (1967) and Rabiner et al (1975).

The DC coefficient is removed by removing the mean of each MUAP before the FFT is calculated. By setting the DC coefficient to zero, the effects of slow base line shifts in the recorded potentials, due to polarization of the electrodes can be reduced and any DC offsets present in the amplification and filtering instrumentation can be removed. The result is a better differential signal representation. The removing of the DC coefficient results in the use of 15 power spectrum coefficients to represent the MUAP's. The advantages of this representation were discussed in the previous section.

The MUAP's are classified in groups of 100. This number is based on available memory and is a convenient group size for quick visual analysis. This number also corresponds to the number of MUAP's which can be continuously collected-compressed by the program detailed in Chapter 3. Each MUAP in the group is assigned a number, from 1 to 100, according to its order of occurrence in time.

The number of active motor units and the numbers of the MUAP's which are to be used as the initial shapes of the MUAP templates for each motor unit are input by the operator. This information is obtained visually by studying the appropriate MUAP's displayed using the routine described in section 3.5. The power spectrum coefficients of the selected MUAP's are used as initial class templates. Automatic classification of the MUAP's, in the present group, to the appropriate motor units is then attempted. Figure 4.3 is a simplified flow chart of the automatic classification process.

4.4.2 Classification By Distance Measure

The distance measure used, as stated in section 4.2.2 is defined by Equation 4.8 and results in a value which is relative to each class template size. The distances are obtained by a subroutine which calculates the distance of a MUAP to each class template and provides a ranking of the closest class to the farthest class. This ranking is contained in a vector, for each MUAP, whose elements are the class or motor unit numbers of the closest to farthest motor units respectively. The first element of the ranking vector, of a specific MUAP, contains the number of the motor unit with the most similar template and so on throughout the vector, with the last element containing the number of the least similar motor unit class.

Before each MUAP is classified, the distances between the current template of each motor unit and the current template of every other motor unit are calculated. For each motor unit, half of the

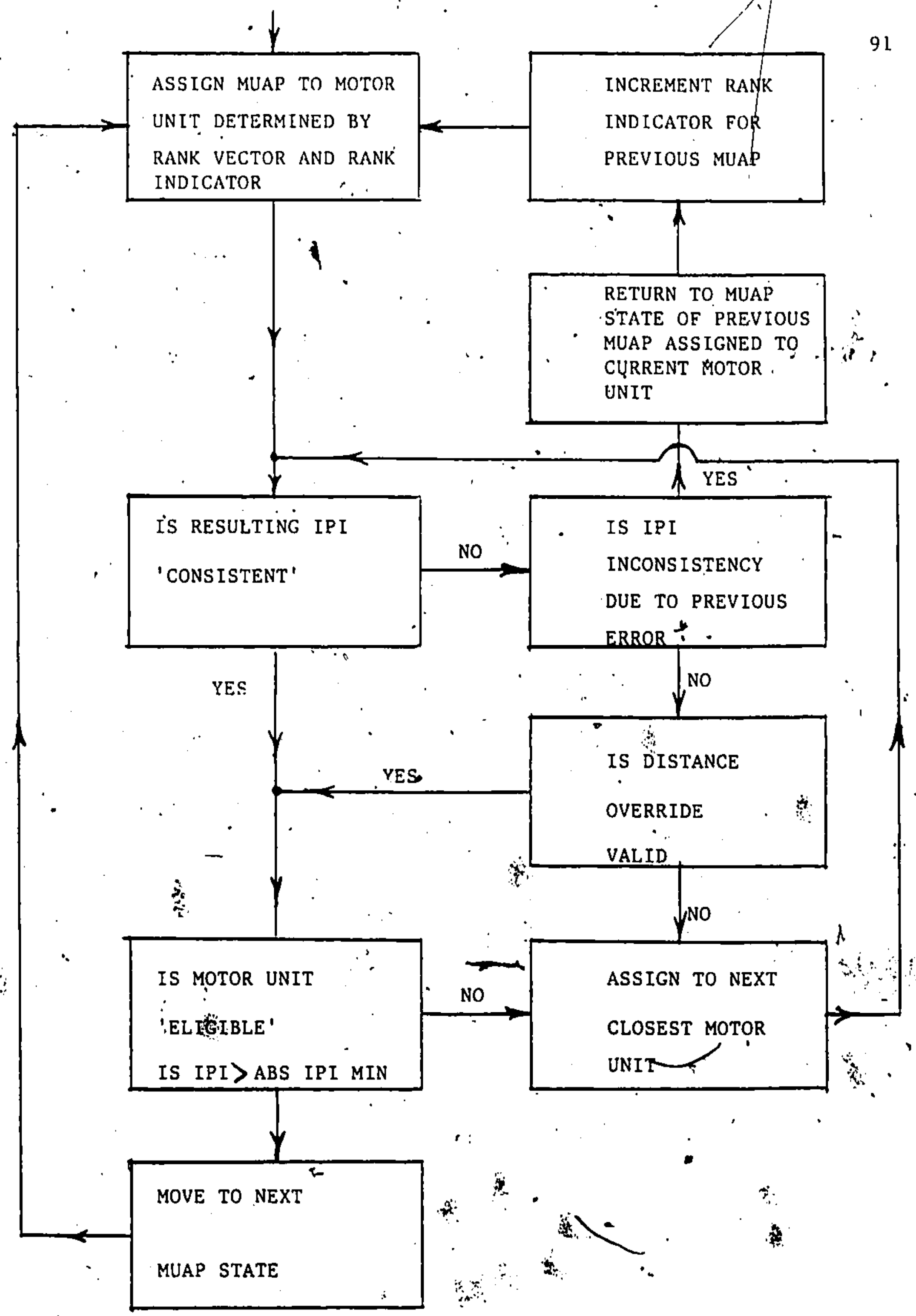


FIGURE 4.3

FLOW CHART OF AUTOMATIC CLASSIFICATION PROCESS distance, to the closest template of the other motor units, is used as a threshold distance for the updating of the template of that class. The template for a class is updated each time a successful classification is made to that class in which the distance of the assigned MUAP to the assigned class template is less than the above mentioned threshold for the assigned class. A class template is updated as a running average of the last five, suitably close, successfully assigned MUAP's to that class. The threshold for updating templates is used to stop similar templates, from different classes exchanging their shapes or flip flopping. The moving average template updating is an attempt to track slow changes in the recorded MUAP shapes due to needle movement.

The order in which the compressed MUAP's are classified follows the order in which they were obtained. The exception to this order occurs when an error in a previously assigned MUAP is discovered when a later MUAP is being assigned. The algorithm accommodates to this by returning to the previous MUAP and reassigning it and all the MUAP's after it with the assignment rules suitably adjusted to account for the previous error. The checking for and handling of potential dependent errors will be explained in more detail later in this section.

The program moves through the MUAP's, assigning each one according to the state of the program at that point. A rank indicator for each MUAP denotes the current distance ranking which is to be used for that MUAP's classification. The rank indicator for each MUAP is initially set to one; this means that each MUAP is initially assigned to the class with the closest template. The first element of the ranking vector for a MUAP, contains the motor unit number, as determined by the distance subroutine, which the MUAP is to be initially assigned to. More generally a MUAP is assigned to the motor unit whose number is contained in the element of that MUAP's ranking vector, which is pointed to by the MUAP's rank indicator. The contents of the ranking vector elements for each motor unit are determined by the distance subroutine, while the value of the rank indicator for each motor unit is determined by the program flow.

4.4.3 IPI Constraints

The rank indicator for a specific MUAP may be incremented if a classification is made which results in an unlikely IPI for that motor unit. After each MUAP is assigned to a motor unit, the resulting IPI for this motor unit is calculated. The IPI is calculated based on timing information obtained from the timing file created for the compressed MUAP with the algorithm described in Chapter 3. If the IPI is greater than the estimated value of the mean IPI minus two standard deviations for this motor unit, then the classification is considered successful and the program moves to the next MUAP state.

If the calculated IPI is less than the estimated value of the mean IPI minus two standard deviations, for this motor unit, an IPI inconsistency has occurred. The term inconsistency is used because such low IPI values should occur less than 2.5% of the time assuming a normal distribution. The program checks if this IPI inconsistency may be due to an erroneous previous or present assignment to this motor unit or if the inconsistency should be accepted.

The distance of the MUAP previously assigned to this class to the template of this class is compared to the distance of the presently assigned MUAP to the same template. The outcome of this comparison determines the subsequent course of action. If the presently assigned MUAP is farther away, its rank indicator is incremented and the classification process continues. This indicates that the present classification, which is based on distance, is not appropriate based on IPI considerations and that the next closest class should be tried for a successful assignment. If the previous MUAP assigned to this class is farther away, the program returns to the state it was in when it was assigning this previous MUAP, with the exception that the rank indicator for this previous MUAP is incremented. This is equivalent to assuming that the previous assignment was an error, based on distance and IPI considerations. The previous MUAP is then assigned to the next closest class and the process continues from this previous state.

Flags are used to determine when returning to a previous state is allowable. The flags avoid cyclical conditions in the flow through the classification process. Returning to a previous state or backing-up during the classification process is accomplished by using the previous IPI mean and variance estimates, which are saved. The rank indicator of each MUAP between the present and the previous state is reset to one during the backing-up process. Other state variables, such as the number of MUAP's in a class, overridable and absolute IPI limits and the appropriate flags must be adjusted.

The above stated IPI constraint is overridable if the distance of the MUAP to the template of the proposed motor unit, the classification which would satisfy this IPI constraint, is twice the distance of the MUAP to the template of the closest 'eligible' motor unit. If this distance criteria is met, the closest 'eligible' motor unit is chosen and the above IPI constraint is ignored. A MUAP assignment, which results in an IPI inconsistency, is thus accepted if the distance of the MUAP to the template of the assigned class for which the IPI inconsistency is created, is sufficiently small compared to the distances of the MUAP to the other class templates.

The term 'eligible' is defined relative to an absolute IPI constraint. The absolute IPI constraint being that all IPI values for a motor unit must be greater than the estimated value of the mean IPI value minus four standard deviations for that motor unit. IPI values below this range have essentially a zero probability of occurring and are therefore absolutely disallowed. A MUAP which, when classified to a particular motor unit, exceeds this absolute IPI constraint is an 'eligible' MUAP for that motor unit.

In summary, when a MUAP classification results in an unlikely IPI for a specific motor unit, the rank indicator of the MUAP farthest away from the template of the motor unit in question, of the last two MUAP's assigned to that motor unit, is incremented and the program continues from this MUAP state. The program is adaptive in the sense that it tries to eliminate any dependent errors. That is, if the IPI inconsistency constraint is violated, the program checks to see if the violation may be due to a previous or presently made error. The program also tries to determine, when an IPI inconsistency is created, if it should be accepted. IPI inconsistency acceptance is via distance criteria.

When more than 100 MUAP's are to be decomposed, the state of each motor unit is made continuous from group to group. The estimates of the IPI mean and variance for each motor unit are passed to the next group. If the number of motor units are the same, the existing templates can be used or new templates can be chosen. If the number of motor units increases, the newly firing motor units will go through the same initialization as at program start-up. The number of the starting MUAP decomposed is incremented by 100. The position of a group in the total collection-compression epoch is then known. The collection-compression was not performed continuously; therefore, the IPI of the first MUAP assigned to each motor unit of a new group is not able to be calculated. First assignments to each motor unit are then based completely on distance criteria and IPI constraints are not used.

4.4.4 Handling Of Unclassified MUAP's

If the rank indicator, for a particular MUAP, becomes larger than the number of active motor units, the MUAP is classified as noise or a spurious compression. For a rank indicator of a specific MUAP to become this large means that, based on IPI constraints, it is unlikely that the MUAP was created by any of the motor units presently being decomposed from the EMG signal.

This classification can also occur from a certain sequence of related errors by the program and the MUAP numbers of the noise classified MUAP's are therefore stored in a vector. At the end of each group of 100 MUAP classifications, an attempt is made to reassign the MUAP's whose numbers are in this vector. Only assignments to motor units ranked first by distance criteria are attempted. The resulting IPI's must be deemed consistent and above the absolute IPI limits as set at the end of the just completed group of 100 classifications. Failure of a successful classification at this point results in the MUAP remaining assigned as noise or a spurious compression. Such classified MUAP's are ignored during any subsequent calculations after the decomposition is completed. Successful assignment at this point results in the MUAP being inserted into the assigned MUAPT and the IPI's for that motor unit being suitably adjusted.

This classification can also occur if the number of motor units active or present in the compressed data is wrongly input by the operator or if only a few firings of a motor unit are compressed. The program, therefore, attempts to account for such situations.

4.4.5 Estimation Of IPI Statistics

Estimates of the mean IPI value and the IPI variance are continually computed based on the IPI values calculated from successful MUAP classifications. The following equations describe the estimates calculated.

$$M_{new} = ((M_{old} \times (N-1)) + IPI_{new}) / N \qquad 4.9$$

$$V_{new} = ((V_{old} \times (N-1)) + (IPI_{new} - M_{new})^2) / N \qquad 4.10$$

where M_{new} is the new mean IPI estimate

M_{old} is the previous mean IPI estimate

IPI_{new} is the IPI of the present assignment

V_{new} is the new IPI variance estimate

V_{old} is the previous IPI variance estimate

N is set to 10 for this implementation

The estimate of the standard deviation is calculated as the square root of the variance estimate.

The initial statistics for each motor unit must be obtained at program start-up. This is accomplished by assigning the first 10 MUAP's to each class, by distance criteria, with very broad and general IPI constraints. The IPI constraints are such that classifications are very close to being based on distance criteria alone. These initial classifications and their resulting IPI values are used to establish the mean and variance estimate for each motor unit.

4.4.6 Handling Of Superpositions

MUAP's as recorded with selective needle electrodes generally occur singularly. The superposition, in time and space, of two or more MUAP's can nonetheless occur. With the SFEMG recording technique used for the data collection in this work, the frequency of superpositions was less then 10%, even at contraction levels as high as 50% maximum voluntary effort. Due to their low number and the time required to resolve their composition, superpositions are simply assigned to a single motor unit. The classification of superpositions proceeds as with all other MUAP's. The fact that the superpositions are left unresolved will result in the missing of some firings of some motor units. This may also happen if a firing is not compressed for some reason. The missed firings of a motor unit will result in the calculation of erroneously long IPI values when a MUAP is next assigned to this motor unit. It is for this reason that the IPI constraints applied during the decomposition are one-sided. The consequences of the existence of erroneously long IPI values in the resulting decomposed IPI data, on the subsequent signal processing techniques used for extraction of information from this data, will be discussed in the next chapter.

4.4.7 Algorithm Output

The output of the decomposition program is a file containing vectors of the results of the classification process. The classification vectors are 100 elements long. Each classification vector element contains the motor unit number which the MUAP, whose number matched the vector element number, was finally assigned to during the classification process. The corresponding classification vector element of MUAP's classified as noise or spurious compressions are set to zero.

The decomposition program will also output to the printer and/or computer terminal pertinent information about the decomposition if requested. The information that can be output to these devices includes file name, detection slope, number of motor units active in the compressed data, initial MUAP numbers used as templates, starting MUAP number, classification vector, MUAP's assigned as noise and the number of the assigned MUAP and the calculated IPI, in the sequence of occurrence, for each motor unit. The distances calculated from each MUAP to each template, the IPI constraints used, the template updating distance thresholds, values of internal flags and the actual order of the classification process can also be printed out if requested.

The file created by the decomposition program along with the timing file and the compressed data file containing the responses from the cannula, are then used to extract the individual motor unit rate coding and morphological information as explained in the next chapter.

CHAPTER 5

RATE CODING AND MACRO EMG ANALYSIS

5.1 Introduction

The extraction of individual motor unit rate coding and macro EMG information requires the analysis of individual motor unit action potential trains (MUAPT's). The individual MUAPT's to be analyzed are calculated by using the classification vectors created by the decomposition program, for single fibre EMG (SFEMG) data, described in Chapter 4, together with the timing file created by the continuous collection-compression routine discussed in Chapter 3.

The classification vectors contain the motor unit number to which each motor unit action potential (MUAP) was assigned. This classification information, accompanied with timing information contained in the timing file mentioned above, allows the creation of each individual MUAPT. These MUAPT's provide a data base from which rate coding parameters for each motor unit can be estimated. The parameters of interest are the mean firing rate and the variance of the firing rate. The mean firing rates of the rate coding process, for each motor unit decomposed from the recorded SFEMG signal, are studied and plotted as functions of time.

The individual MUAPT's, together with the compressed responses from the cannula, provide the necessary information to create synchronously averaged macro motor unit potentials (MUP's) for each motor unit, similar to those introduced by Stalberg (1980). The compressed cannula responses are in a file created by the program outlined in Chapter 3.

This chapter discusses the signal processing techniques used to extract the rate coding information. The methods used to account for unresolved superpositions and a less than completely accurate decomposition are explained. The definition and presentation of the rate coding parameters estimated are included. The chapter also deals with the calculation of macro MUP's for each motor unit. The techniques used for these computations, the macro MUP parameters measured and the format of their display are described.

5.2 Rate Coding

The extraction of rate coding information from the decomposed SFEMG signal is effected by a separate Fortran program. The program reads the classification vector file and the timing file. Using both of these files, the program can construct the MUAPT's of each motor unit represented in the classification vectors. The MUAPT for each motor unit is stored in a vector, as a sequence of inter pulse interval (IPI) values. The number of motor units or number of IPI vectors required, is determined from the text header in the timing file, which is updated by the decomposition program.

The decomposition process is not completely accurate. Unresolved superpositions of MUAP's, wrongly classified MUAP's and MUAP's which were not compressed, can all lead to the existence of erroneously long IPI values. Wrongly classified MUAP's can also lead to erroneously short IPI values as well. In an attempt to recognize and compensate for the IPI errors existing in the data, the IPI data is filtered. The filtering of the IPI data tries to locate and remove IPI errors by replacing unlikely IPI values with more appropriate IPI values. The unlikely IPI values are identified by comparison to an expected range of IPI values, determined by estimating the current probability distribution of the motor unit firing times.

The IPI data for each motor unit is initially scanned by the program to find a section of data for which a mean IPI estimate, free of errors, might be obtained. A suitable section of IPI data is found when a section of 10 consecutive IPI's are within a range, defined as plus or minus 30% of the current first IPI of the section. If one of the IPI's in the current section is outside this range, the start of the section is moved up one element in the IPI vector. In this way, the IPI data for each motor unit is searched for a section which has a low probability of containing any gross IPI errors. Sections containing relatively long or short IPI values, which may be due to the errors mentioned above, are avoided. Errors created by misclassifications which resulted in minor IPI errors might still be present. The low number and minor nature of these errors, however, will not greatly affect the mean IPI or IPI variance of the section. The plus or minus 30% range was empirically determined to be optimum for the data studied.

When a suitable section in the IPI vector is found, an initial mean IPI is estimated as the average IPI of the section. The variance of the IPI's of the section is also calculated based on this mean IPI estimate. These values are then used as seeds to initialize the criteria for the filtering of assumed errors from the IPI data. If a suitable section is not found, subsequent IPI processing for that motor unit is not performed and the motor unit is deemed too variable.

Starting at the IPI, immediately before the beginning of the suitable section found in the above defined search and working back to the beginning of the IPI vector, all IPI values outside a defined range of IPI values are replaced by an approximation of the current IPI. The filtering process is then applied to IPI values from the beginning of the chosen section to the end of the IPI vector.

The acceptable IPI range is defined by the current value of the mean IPI estimate plus 3 standard deviations or minus 3.5 standard deviations. The range is not symmetric about the mean value and was determined empirically. It favours low IPI values and is more restrictive to high IPI values. This reflects the fact that the unlikely low IPI values have been previously scrutinized by a distance criteria in the decomposition algorithm, (see Section 4.4), and that unlikely long IPI values due to superpositions are known to exist and must be removed. The standard deviation is calculated as the square root of the current variance estimate. The mean IPI and the IPI variance are continually estimated by running calculations similar to Equations 4.5 and 4.6, but with N equal to 20. The initial mean and variance estimates, obtained from the section chosen during the search, are used to define the accepted IPI range at the start of filtering, in both directions.

IPI values replaced by the filtering criteria are not included in the running mean and variance estimates. This causes a bias in the variance estimate towards smaller variance estimate values. This bias is due to the rejection of any true IPI values which might occur that are outside the accepted range. A bias of the mean estimate towards lower mean estimate values is also believed to be present due to the lack of symmetry of the acceptance range. These biases are not large and are justified on the basis of number of true errors that are accounted for by the filtering technique. The number of errors introduced by the error filtering is small due to the low probability of a true IPI being replaced, even though the true probability of the replaced IPI's is higher than indicated by the ranges chosen. This is due to the biases existing in the mean and variance estimates.

The approximation of the current IPI value, which is used to replace IPI values thought to be erroneous, is dependent on the nature of the believed IPI error. If the IPI to be replaced is below the current estimate of the mean IPI or less than 4 current standard deviation estimates above it, the IPI value is replaced by the current mean IPI estimate. If the IPI to be replaced is greater than 4 current standard deviation estimates above the current mean IPI estimate, it is assumed to be due to a missed firing of the motor unit. This is probably due to an unresolved superposition, but might also be due to a missed MUAP compression. The number of firings missed is estimated and the IPI is replaced by its value divided by the number of estimated missed firings. This results in an 'instantaneous' mean IPI value. The number of missed firings is determined as the value of NMF which minimizes X in the following equation.

$$X = (IPI_r / NMF) - IPI_m \quad (5.1)$$

where IPI_r is the IPI being replaced.

IPI_m is the current mean IPI estimate

NMF is the number of missed firings

X is the quantity to be minimized.

For all the IPI values replaced, the replaced IPI value, the current IPI mean and IPI variance are stored in error vectors for later analysis or print out if required.

The error filtered IPI data for each motor unit is then low pass filtered to obtain an instantaneous smoothed IPI value. The reciprocal of this IPI value is used to represent the instantaneous average firing rate for the motor unit. These firing rates for each motor unit are then plotted versus time. The force output during the contraction, continuously collected and stored, by a separate program, in a separate file, can also be plotted on the same graph. Figure 5.1 is a typical plot.

The low pass filtering of the error filtered IPI data is effected by convolving the error filtered IPI data vectors with a symmetrical Hamming data window whose impulse weights are normalized (Oppenheim and Schafer 1975). The length of the data window is variable. This allows for different degrees of smoothing as determined

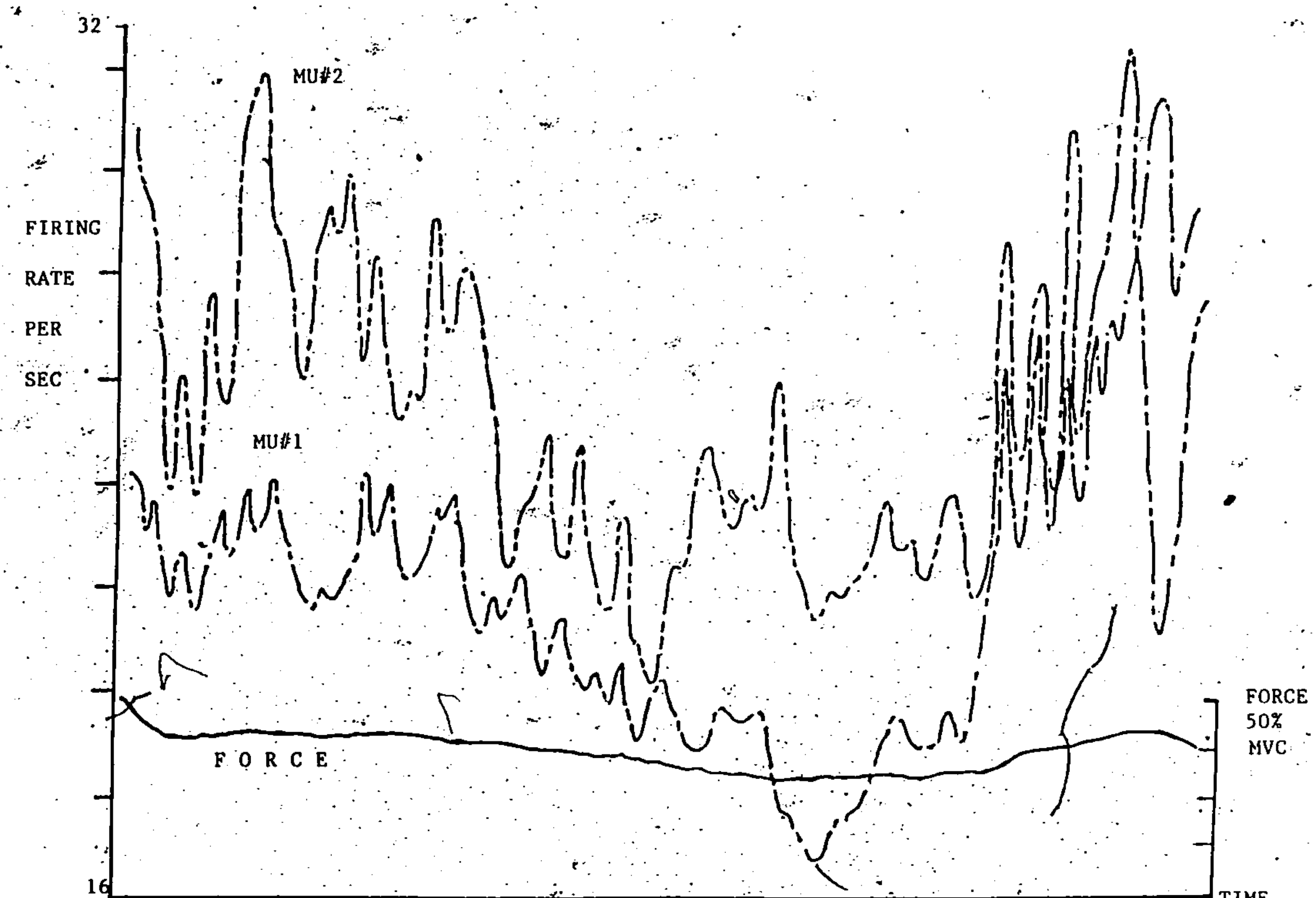


FIGURE 5.1
TYPICAL RATE CODING ANALYSIS OUTPUT

by the operator, to reflect different time constants of rate coding.

5.3 Macro EMG

The classification vectors created by the decomposition program outlined in Section 4.4, together with the compressed responses of the cannula obtained by the program of Chapter 3, provide the basis necessary for calculating a macro MUP for each motor unit decomposed from the SFEMG signal. The calculation of the macro MUP's is performed by a separate Fortran program.

The program reads the classification vectors created during the decomposition of the SFEMG signal and the compressed data file containing the cannula signals created during the collection-compression run. MUP vectors, one for each motor unit, equal in length to the number of cannula compressed data samples, are used to construct the macro MUP's. Each successive compressed epoch of cannula signal is ensemble added to the appropriate MUP vector as determined by its motor unit classification number contained in the classification vector. The number of epochs summed for each motor unit is stored. After all the elements of the classification vectors are accounted for, the MUP vectors for each motor unit are divided by the number of additions made to each vector. The resulting ensemble average is the macro MUP for that motor unit. The resulting macro MUP's are plotted. Their areas and peak to peak voltages are measured and displayed. Figure 5.2 is a typical result.

MOTOR UNIT NO. 1
NO. IN AVG. 697
AREA - 2.36 μVS
Vpp - .75 mV

MOTOR UNIT NO. 2
NO. IN AVG. 699
AREA - 2.14 μVS
Vpp - .72 mV

MOTOR UNIT NO. 3
NO. IN AVG. 102
AREA - 2.45 μVS
Vpp - .87 mV

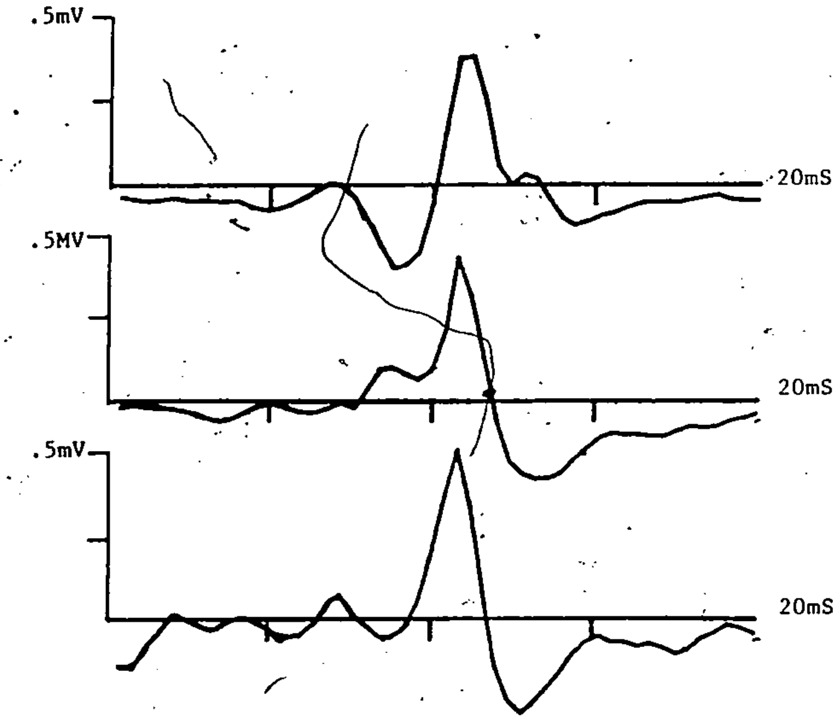


FIGURE 5.2
TYPICAL MACRO EMG ANALYSIS OUTPUT

The SFEMG decomposition is suitably accurate, the number of superpositions is small enough and the number of cannula responses for each motor unit macro MUP is large enough, that error filtering such as performed in the previous section is not necessary. The mean value of each compressed cannula response is subtracted from each sample of the response before averaging is begun. The resulting compressed cannula responses then have zero mean values. This is to reduce the effect of any slow base line fluctuations that might occur during signal recording, due to electrode polarization and any DC bias that might be present in the recording instrumentation.

The signal recording and collection-compression protocol and the signal decomposition and data analysis techniques introduced in the last four chapters were used to analyze EMG data obtained during various muscle contractions of human hand muscle. The following chapter describes these data collections and discusses the results and accuracy of the signal decomposition and data analysis.

CHAPTER 6

PERFORMANCE OF RECORDING AND ANALYSIS PROTOCOL

6.1 Introduction

The previous four chapters introduce a new signal recording and data analysis protocol to obtain individual motor unit rate coding and morphological information from an EMG signal. This protocol was used to collect and compress EMG signals recorded during various isometric contractions of human muscle. The compressed data were then decomposed and the rate coding and morphological information were extracted.

This chapter outlines the details of these data recordings, collection/compressions and the subsequent data analyses. The techniques used to determine the accuracy of the performed decomposition and error filtering analyses are reported along with their actual accuracies. The expected accuracy of the analysis procedure in general is discussed. Comparisons are made with similar analysis techniques and the overall process performance is reviewed.

6.2 Signal Recording

The muscle selected to record EMG signals from was the first dorsal interosseous (FDI). This muscle was selected for a number of reasons. It is a relatively easy muscle to locate with an inserted needle electrode. It produces force by the early use of recruitment

(Milner-Brown 1973c), a fact which improves the chances of recording multi-unit SFEMG signals, even at low levels of force. It is the only muscle involved in moving the index finger away from the middle finger (Milner-Brown et al 1973a), therefore simplifying the isolation and measurement of the forces it produces.

The EMG signals were sensed, amplified and filtered using a standard Teca single fibre needle electrode and a Teca T4 EMG machine. The SFEMG signal was the voltage created between the selective surface of the needle relative to a distant surface plate electrode. The cannula potentials were measured from the needle cannula relative to the same distant surface plate electrode. A distant surface plate electrode was also used as a ground to reference the subject to the amplification equipment. While recording from a FDI muscle, the distant surface plate electrodes were located over inactive tissue at the elbow of the same arm.

The SFEMG and cannula signals were separately differentially amplified by Teca PA63T preamplifiers and simultaneously fed into individual Teca AA6 MKIII amplifiers. Both amplifiers were set at a .5 mV/Div sensitivity which corresponds to an overall gain of 1000 for each signal. The SFEMG signal was band pass filtered with a pass band of 500 Hz to 5 KHz, the cannula signal having a pass band of 8 Hz to 1.25 KHz.

The force produced during a contraction was measured by a force transducer. The force transducer was effected as a full bridge circuit arrangement of 120 ohm strain gauges powered at a 5 V DC level. The center point of each bridge leg provided the reference points for the measurement of the force transducer's output. The force transducer was built as part of a restraining device. The restraining device was designed to minimize movement of the hand and index finger to produce muscle contractions as isometric as possible. The force measurement system and restraining device is shown in Figure A1.5.

The force signal was the amplified and filtered output of the force transducer. The amplifier gain was 1000 and the force signal was low pass filtered with a 10 Hz cutoff frequency. The force signal amplification and filtering was performed by the MUAP detection hardware as described in Appendix 1.

The subject's amplified and filtered force output was displayed on an oscilloscope screen along with the desired force target range. The force target range was produced by the MUAP detection hardware as outlined in Appendix 1. Each subject's maximum voluntary force output was determined at the beginning of each recording session. Force levels were then set relative to this limit. The force target range was positioned at the desired constant force level or was allowed to sweep through an appropriate triangular force pattern. The subject was instructed to maintain a force within the displayed force target range.

The force protocols used during collections varied from constant force isometric contractions at 25 or 50% of the subject's maximum voluntary contraction (MVC), to triangular force varying isometric contractions to peak force levels of 25 and 50% MVC. Triangular force varying isometric contractions about a mean contraction level of 25% of MVC were also tried.

Efforts to ensure the stationarity of the recorded data were made by assessing needle movement using SFEMG signal slope and amplitude criteria, as discussed in section 2.6. The thresholds used were an amplitude of 1.2 mV and a slope of 6 V/s. With the subject producing minimal force, the needle was moved gently about until the acquired SFEMG signal exceeded these thresholds. Flashing of the three LED's of the MUAP detection hardware were used to indicate this condition. With these lights flashing, the desired contraction was performed. If the LED's did not continue flashing throughout the contraction, needle movement was considered unacceptable, the recorded data was discarded and the contraction was repeated. Rest periods were inserted between consecutive muscle contractions to avoid fatigue. The amplified and filtered signals (SFEMG, cannula and force) were recorded on magnetic tape using a Hewlett Packard 3964A instrumentation recorder at a tape speed of 15 in/s. Figure 6.1 shows the recording setup.

6.3 Data Collection-Compression

The signals recorded on FM tape were played back at a tape speed of 3 3/4 in/s. This corresponds to an expansion of the playback time base by a factor of four compared to the record time base. The speed reduction was necessary due to collection-compression program limitations discussed in section 3.4.

Both the SFEMG signal and the cannula responses were compressed. The collection sampling rate was 2.5 KHz and the collection compression sampling ratio for the second channel was set at 4. This resulted in an

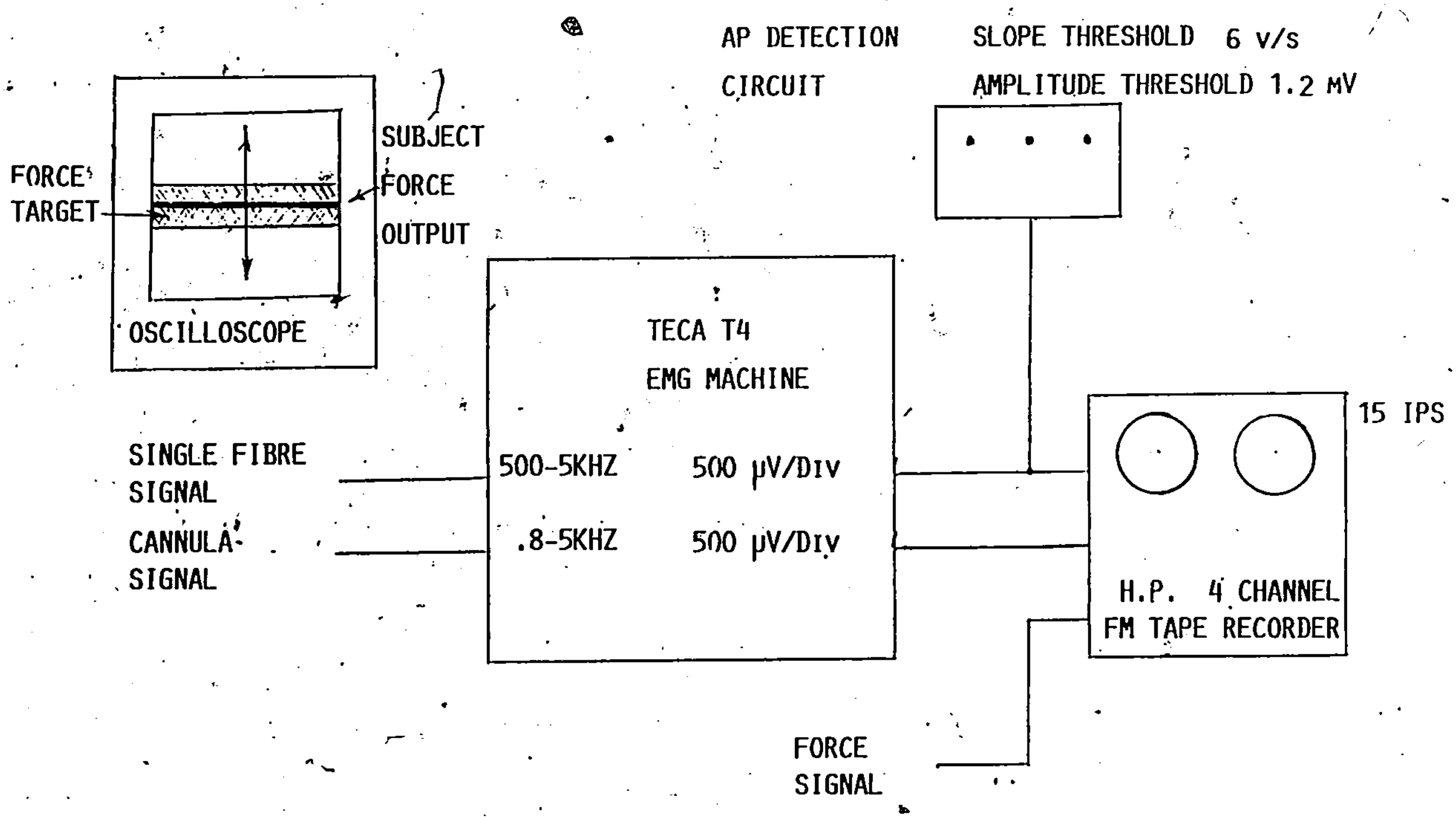


FIGURE 6.1

SIGNAL RECORDING SET UP

effective compression sampling rate of 10KHz for the SFEMG signal and 2.5 KHz for the cannula channel.

The number of samples compressed for each MUAP detection for both channels was set at 50. The stored data then included a 5 ms long representation of the SFEMG MUAP, accompanied by a 20 ms long concurrent epoch of the cannula signal.

The minimum time allowed between successive MUAP detections was set at 1 ms. MUAP's occurring within this time limit relative to a previous MUAP would not be compressed and would be considered a superposition. Most occurrences of this nature were visible when the SFEMG data was displayed. The maximum number of MUAP's compressed during one run was 1500. This limit is dependent on the timing buffer length as explained in section 3.4. The slope criteria was set at 4 V/s and the amplitude threshold was .2 mV. The playback/record switch of the MUAP detection hardware was in the playback position to account for the difference in the playback and record tape speeds (see Appendix 1).

6.4 Data Analysis

For each set of compressed data, the shapes of the SFEMG MUAP's were visually assessed using the display program outlined in section 3.5 to determine if the data were suitably stationary and if manual or automatic template initialization between groups was appropriate. If the data was considered too nonstationary, processing did not continue. The visual assessment is a further check for needle movement and detects movement not apparent during the recording, possibly due to alternation of recorded MUAP shapes both of which satisfy the recording movement criteria.

This visual assessment also allows the operator to determine the number of motor units active in the compressed data and to select representative initial template shapes. If the data had some shape changes or if the number of active motor units changed from group to group, manual template updating and re-initialization between groups of decomposed MUAP's was used. This means that for each group of 100 MUAP's decomposed, the number of templates and their initial shapes are input by the operator. If the data was very stationary and the number of motor units active remained constant, the number of templates and their initial shapes for subsequent groups after the first group, was automatically determined by the program.

The time to analyse a group of 100 MUAP's varied from 2 to 3 minutes depending on the number of motor units active. This time includes the time to Fourier transform the SFEMG data, calculate the power spectrum coefficients, initialize the templates and assign the MUAP's to the appropriate motor units. Error filtering and plotting of the resulting IPI data and the creation and display of the macro MUP's was performed only after the complete compressed data set was decomposed. The time required for these analyses was 2 to 4 minutes depending on the total number of MUAP's in the data set decomposed. The total time required to analyze a compressed data set of 1000 to 1500 MUAP's, from 2 to 5 active motor units, ranged from 30 to 40 minutes. These data sets were from muscle contractions of 30 to 40 seconds duration depending on the level of muscle activation. This converts into processing time versus data time ratios in the .75 min/s to 1.25 min/s range.

6.5 Typical Results

Initial data collections were used to test and develop the system. Following final development of the collection protocol and analysis algorithm, a series of data collections were performed for each of three normal male subjects. The contraction protocols included constant, ramped or modulating force levels as described previously.

For constant contractions at high force levels (greater than or equal to 50% MVC) or those with rapidly changing force, needle movement restricted the number of contractions, suitable for data collection, to between 20 and 30% of the number of contractions attempted. This could be improved with increased experience on the part of the investigator and a better method of securing the needle electrode. At present, it is held manually by the investigator during the contractions.

Ten records obtained using different protocols were analyzed. Figure 6.2 and 6.3 show the motor unit firing rates and macro MUP's, respectively, resulting from the processing of data, recorded during a constant, 25% MVC, force contraction. Figure 6.4 and 6.5 similarly show the results of the analysis of data, obtained during a triangular-shaped force contraction with a peak force of 25% MVC. Figure 6.6 and 6.7 depict results from a contraction which had a modulating force output about a mean force level of 25% MVC.

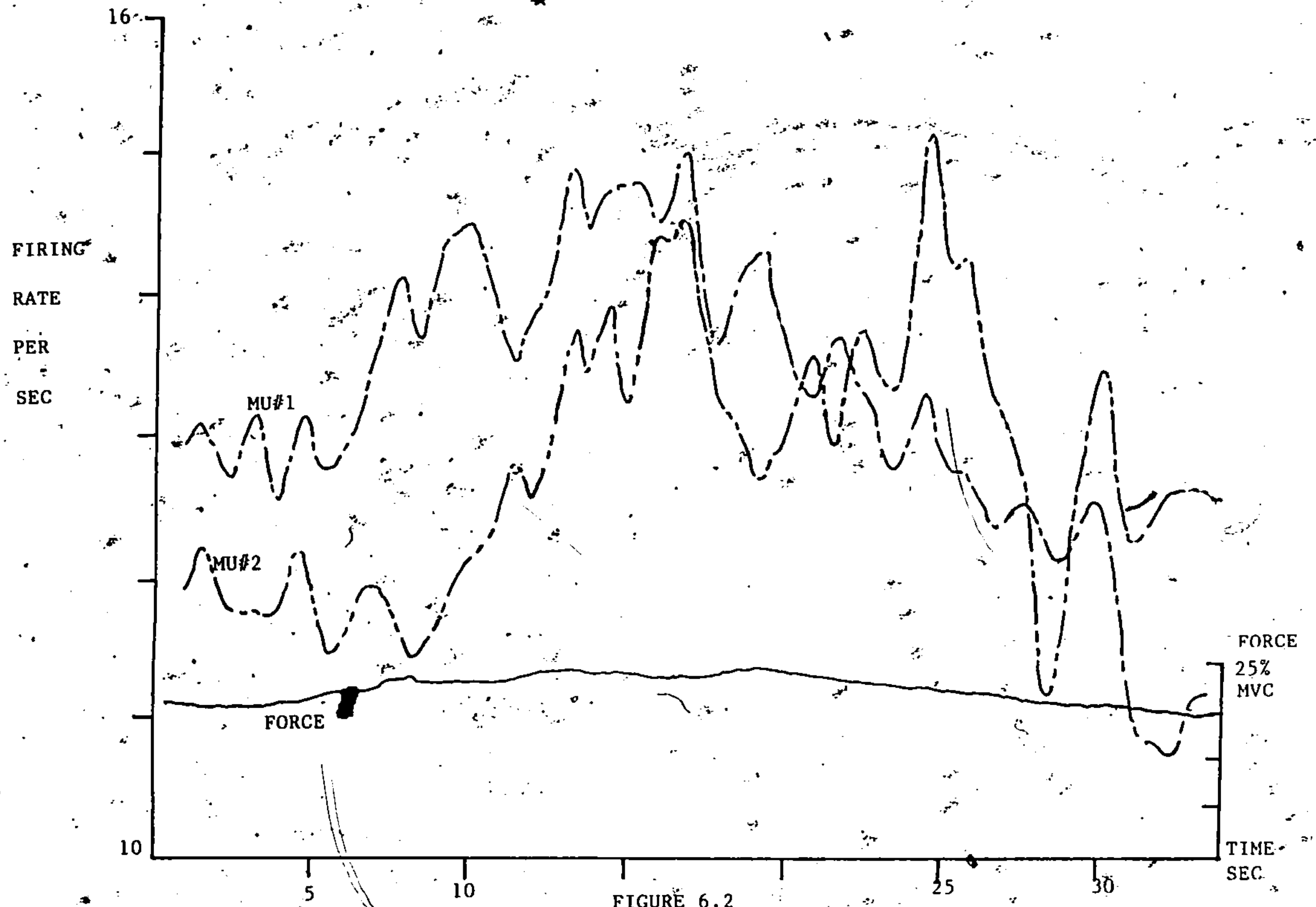


FIGURE 6.2
RATE CODING ANALYSIS OUTPUT - CONSTANT 25% MVC

MOTOR UNIT NO 1
NO. IN AVG. 419
AREA 1.19 μVS
Vpp - .75 mV

MOTOR UNIT NO. 2
NO. IN AVG. 424
AREA 1.25 μVS
Vpp .62 mV

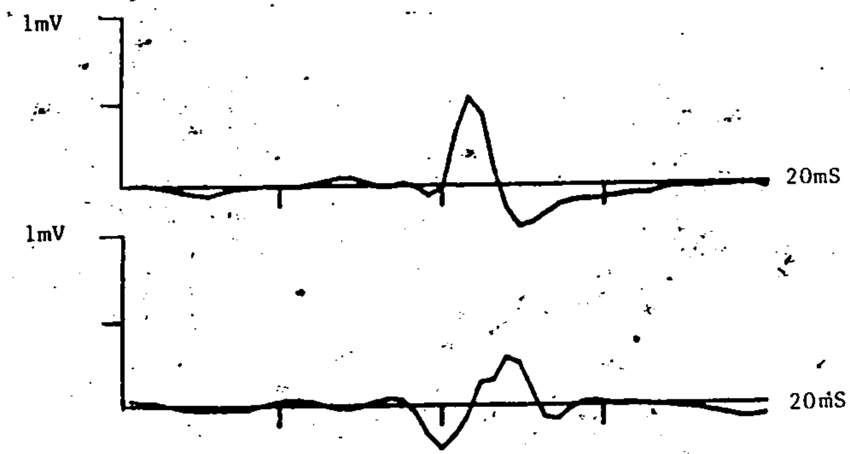


FIGURE 6.3
MACRO EMG ANALYSIS OUTPUT - CONSTANT 25% MVC

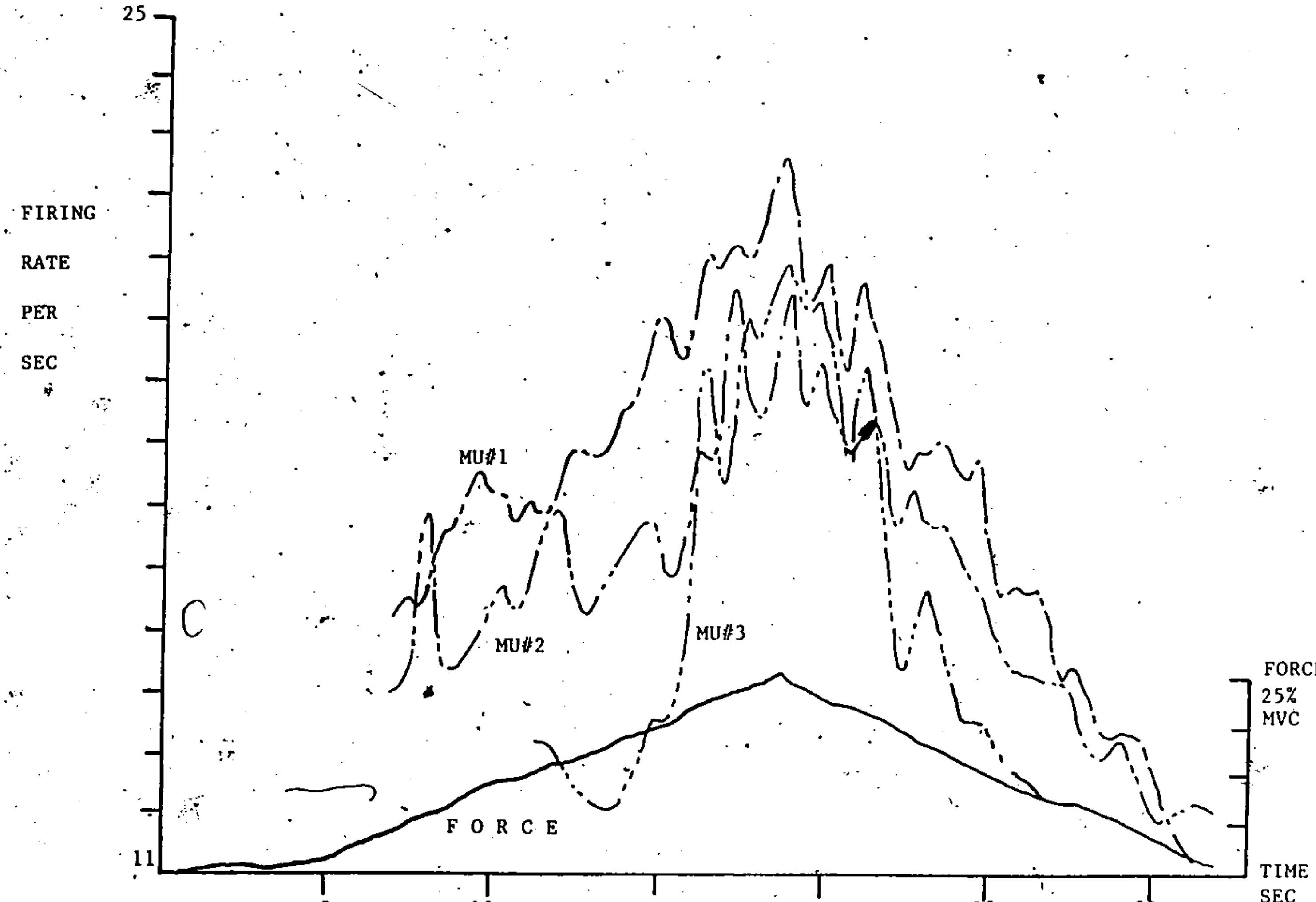


FIGURE 6.4
RATE CODING ANALYSIS OUTPUT - RAMPED TO 25% MVC

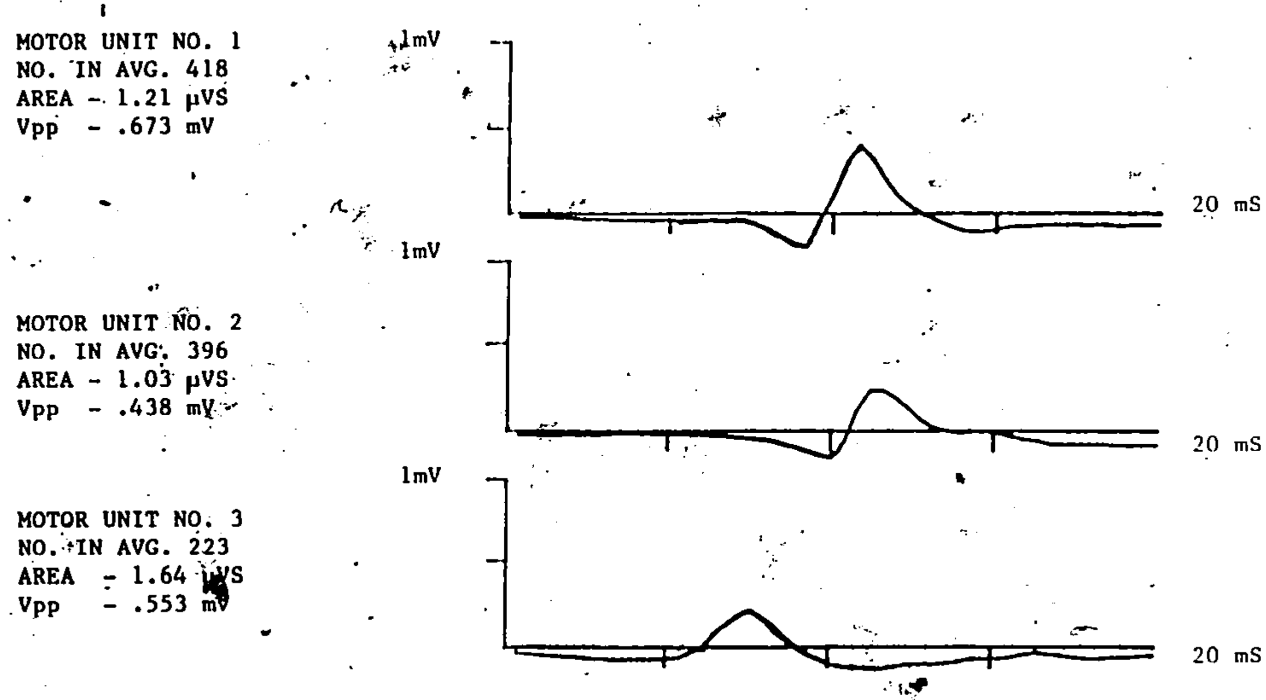


FIGURE 6.5
MACRO EMG ANALYSIS OUTPUT - RAMPED TO 25% MVC

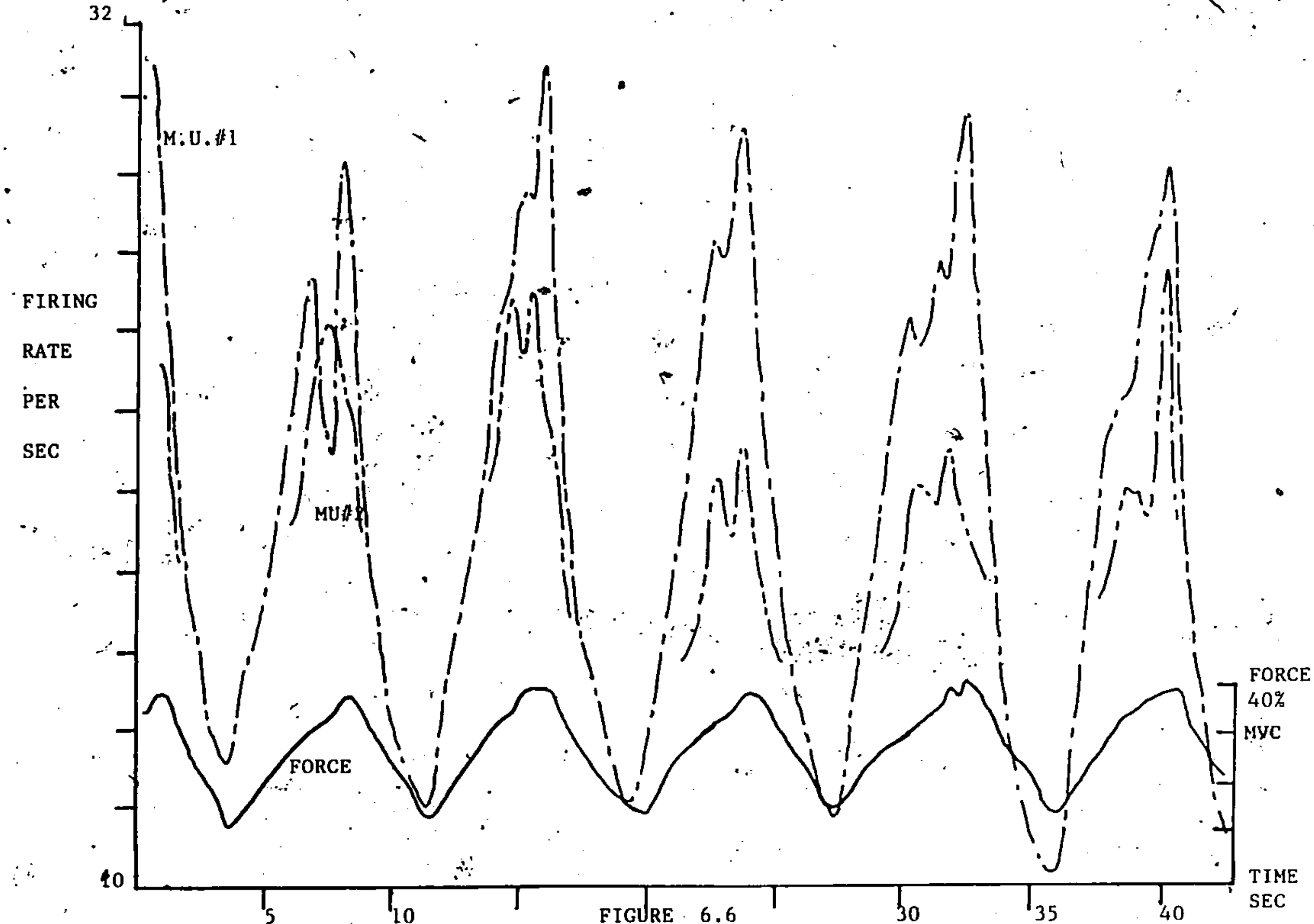


FIGURE 6.6
RATE CODING ANALYSIS OUTPUT - MODULATED ABOUT 25% MVC

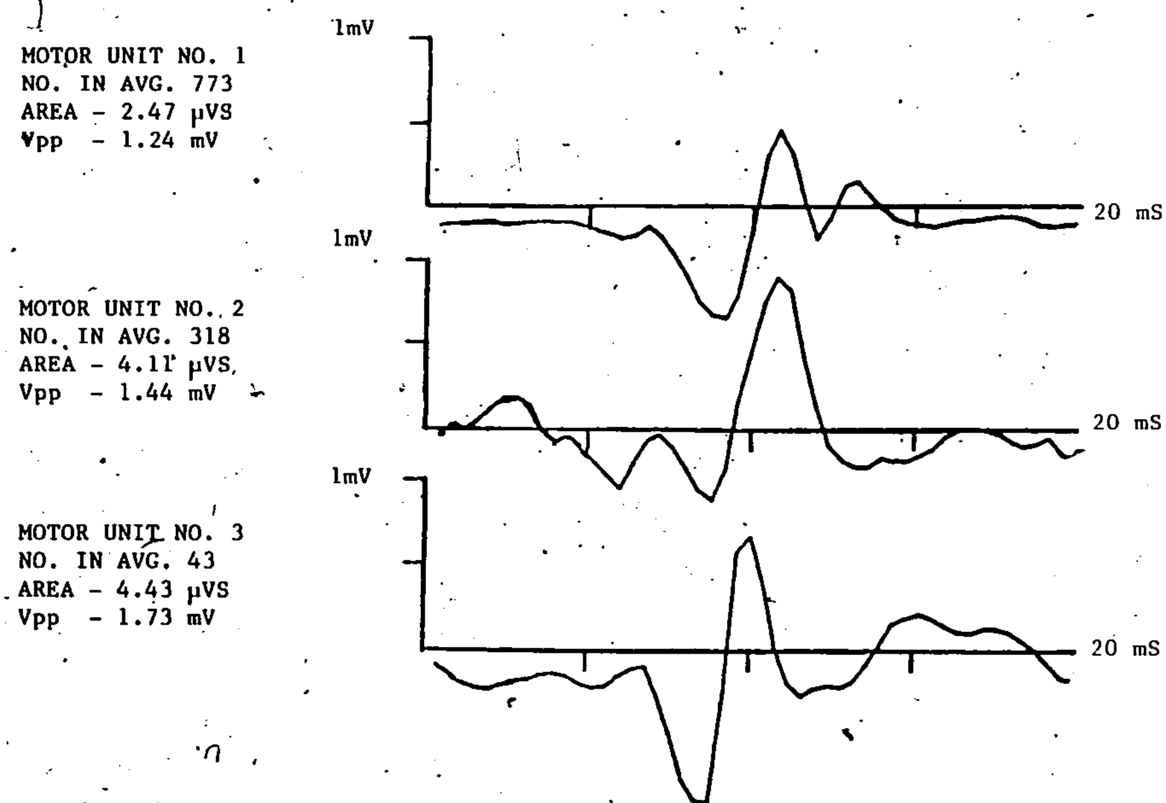


FIGURE 6.7

MACRO EMG ANALYSIS OUTPUT - MODULATED ABOUT 25% MVC

6.6 Validity Assessment

Heetderks (1978) proposed a method of determining the expected accuracy of a data classification scheme based on an apparent separation matrix. Examples cited developed separation matrices for classification schemes which had low dimensional feature spaces. The calculation of separation matrices for classification schemes which use large numbers of features is untenable. Other assumptions made regarding the probability distributions of the features also rule out the use of this technique to assess the accuracy of the decomposition process introduced.

The accuracy of the decompositions of the compressed data were then determined by comparison to manual decompositions of the same data. The collection-compression process, as discussed in section 3.4, was found to be essentially 100% accurate. Therefore, the manual decomposition of the compressed data was considered the gold standard with which the automatic decomposition results could be compared to determine their accuracy. Each MUAP assignment determined by the program was then compared to the manual classification of the same MUAP and discrepancies noted. The program decomposition was found to agree with the manual assignment more than 95% of the time.

The results of the error filtering were assessed by studying the percentage number of superpositions accounted for, the number of true IPI values replaced and the number of IPI errors overlooked. Superposition occurrences were determined by visual inspection, using the display program described in section 3.5, of the compressed SFEMG

MUAP's for the data sets analyzed. True IPI values were determined by the manual decomposition and IPI errors were also determined relative to the manual assignments.

Five data sets, each with at least 1000 MUAP's, were exhaustively analyzed and all of the superpositions were accounted for by the error filtering. The number of true IPI's discarded and the number of IPI errors overlooked varied for each data set but was in the 1% range for each. The final IPI data were found to be better than 97% accurate.

The general expected accuracy of the decomposition-error filtering process is dependent on the quality of the compressed data. The quality of the data is determined by its signal to noise ratio, stationarity and the actual separation of the motor unit class templates. If any one of these aspects of the compressed data is degraded the process accuracy will suffer. Notwithstanding these data constraints, it is believed that suitable data can be readily collected using this recording protocol and that overall procedure accuracy above 95% can be routinely obtained.

6.7 Comparison And Overall System Performance

Other methods of decomposing multi-unit records for the extraction of IPI information have been reported. Gath (1975) used temporal information to extract individual motor unit action potential trains (MUAPT's) from composite EMG signals. He applied separate comb-like time filters, with specific properties for each MUAPT to be extracted. The filter properties were obtained from the EMG power spectrum. The process was reported 80% successful and a separate run had to be performed for each MUAPT to be obtained.

Dinning and Sanderson (1981) and Abeles and Goldstein (1977) relied on shape differences to differentiate action potential classes. Dinning and Sanderson used a reduced feature set to allow real time classification. Abeles and Goldstein used feature templates calculated based on a principle components analysis of the data. Both techniques were applied on neural spike trains.

LeFever and De Luca (1982) presented an EMG decomposition scheme that was based on maximum likelihood detection theory. The classification criteria was a weighted sum of the MUAP's similarity to a proposed class template and the probability of that motor unit firing. The MUAP's were recorded concurrently, from multiple selective lead off surfaces and MUAP shape comparisons were performed using the multiple channel MUAP representations. The process was interactive with the operator and fully resolved all superpositions of MUAP's. The technique has the capability of 100% accurate decomposition of an EMG signal with up to 8 active motor units. The processing time versus data time ratio was reported to typically range from 5 min/s to 30 min/s, and could go as low as 1 min/s for simple composite EMG signals. An experienced operator is necessary for successful results. The technique was revised by Mambrito and De Luca (1983) to be more efficient and require less processing time, while maintaining the decomposition accuracy.

The decomposition technique developed and presented here, while unique, is most similar to the latter method described. It utilizes both MUAP shape and firing probability criteria to decompose the EMG signal. The MUAP's are registered with a single recording surface to reduce signal processing time. The handling of the unresolved superpositions and decomposition errors by the attempted error filtering is a new approach to these problems.

Calculating macro MUP's from decomposed EMG signals allows several motor unit macro MUP's to be obtained from one contraction. This allows higher threshold motor units to be examined. The accuracy of the calculation is similar to that obtained by existing clinical processes. The number of superpositions and classification errors do not significantly affect the results. This is because of the small number of errors and superpositions compared with the large number of cannula responses averaged.

The accuracy of the data resulting from the decomposition and error filtering process is sufficient to reliably determine the motor unit mean firing rates and firing rate variances. The plotted Hamming windowed IPI data can be used to observe trends in the firing rates and their variances. Evidence of rate coding with changing levels of force, common motor unit drive (De Luca et al 1982b) and motor unit potentiation (the decrease in a motor unit's firing rate shortly after the initiation of an isotonic contraction) can be seen in the firing rate plots.

Increases in the firing rates and the loss of a common drive for the motor units (the alternating of motor unit firing rates, one motor unit increasing its firing rate while another motor unit decreases its firing rate) at late stages of isotonic contractions, thought to be effects of fatigue, have also been observed with the firing rate plots. The number of contractions and the size of the population of motor units studied is not sufficient however to confirm any of these observations as actual phenomena of physiological fatigue.

Due to the decomposition errors and the unresolved superpositions, and the error filtering estimates used to account for them, serial correlations and cross correlation studies of the resulting IPI data are not accurately obtainable. Exact firing rate information at any specific time during a contraction is also not available.

The procedure is valuable but not without inherent limitations. The following chapter outlines the procedure's value and limitations. It deals with possible solutions for some of these limitations and discusses the possible future applications of this procedure emphasizing its clinical potential.

CHAPTER 7

CONCLUSION

7.1 Introduction

Details of a new procedure for the automatic extraction of individual motor unit rate coding and morphological information have been presented in the preceeding chapters. This chapter summarizes the value of this procedure, points out its present limitations and suggests possible future uses. Possible revisions and or additions to the process to overcome its present limitations are discussed. The application of the technique, or revised versions of it, to aid in clinical diagnosis is hypothesized. Parameters of the rate coding and morphological analysis which might prove to be clinically useful are proposed and the need for further research in this area is stressed.

7.2 System Value and Limitations

The procedure developed meets the objectives set at the beginning of this work. The technique can successfully record an EMG signal from human muscle and semi-automatically obtain and display individual motor unit rate coding and morphological information pertaining to the motor units present in the recorded signal. The analysis is suitably accurate and can be performed with moderate operator effort in a reasonable length of time. The time required for the analysis could be significantly reduced (by factor of 10), if alternate hardware were used to perform the data collection-compression, Fourier transformations and power spectrum calculations and the calculation and comparison of feature space distances.

The analysis provides, simultaneously, information about the size and firing rates of the motor units contained in the compressed SFEMG signal. This combination of information allows studies relating motor unit firing rates to motor unit size, to be efficiently performed. Where Milner-Brown et al (1973a), obtained the motor unit twitch tensions and therefore their inferred size, by synchronously averaging the force record, macro MUP's provide motor unit size information, by averaging the cannula response. This data can then be readily correlated with the firing rate data.

Other techniques of decomposing the EMG signal deal basically with more complex composite signals. The use of the SFEMG electrode allow one to record signals which are sufficiently complex to provide some useful information, but are still simple enough to allow accurate decomposition with moderate signal processing effort. When using highly selective electrodes, the individual motor unit information exists in an EMG signal that is not too complex or superimposed to make decomposition and information extraction too difficult.

The individual MUAP's obtained with highly selective electrodes are composed of the contributions from only a few fibres of the motor unit. Each contributing fibre has a specific geometry relative to the electrode and its contribution can be seen in the recorded MUAP shape. Therefore, the MUAP for each motor unit is quite unique and of short duration. The composite EMG signal is then composed of a few uniquely shaped, short duration MUAP's. The small number of motor units and the short duration of their MUAP's result in few superpositions.

Less selective electrodes have MUAP's composed of contributions from a larger number of fibres of a motor unit, than those recorded with highly selective electrodes. The averaging of the individual fibre contributions result in longer duration MUAP's. The resulting EMG signals are composed of longer duration MUAP's from a larger number of motor units. The potential for superpositions is greater. Therefore, EMG signals obtained with less selective electrodes, contain more information about more motor units per se, but the extraction of individual motor unit information is sometimes very hard or impossible due to temporal and spatial overlap of the component MUAP fields.

The use of selective SFEMG needle electrodes is also the source of some of the procedure's limitations. With selective recording surfaces, electrode movement can greatly affect the recorded signals. This nonstationarity must be minimized and tracked or the decomposition scheme performance suffers. Needle movement is a problem which must be overcome with all decomposition schemes, but it is most important when using very selective electrodes.

The decomposition scheme presently utilizes a moving average of acceptable templates in an attempt to track the moving template shapes. More sophisticated signal processing techniques might be used in this area. Struder et al (1984) proposed adaptive Kalman filtering to track the changing states of the class templates. Similar filtering techniques or other adaptive procedures could be evaluated.

Another method of reducing needle movement is to use less selective or bipolar needle electrodes. Notwithstanding the above discussion about needle selectivity, slightly larger recording surface areas can be investigated. Bipolar electrodes might also be advantageous. They can achieved selective recordings even with relatively large recording surfaces because of the differencing which they perform. The large recording surfaces would then reduce movement effects.

The size of the population of motor units sampled with the SFEMG electrodes is limited to about five and is more typically three. This population size can be increased by recording with a linear array of electrodes simultaneously. Each channel of the array sampling a separate muscle area. Using an array electrode would also allow motor unit territories and conduction velocities to be estimated.

Initial attempts at multi-channel recording techniques have been performed with a five channel electrode, four selective surfaces and the cannula. The electrode has a 0.45 mm cannula, with four 0.050 mm diameter selective lead off surfaces, positioned 0.6 mm apart, in the plane of the cannula surface, starting 15 mm from the tip. Recordings from each channel are relative to a single distant surface reference.

The increased recording surface areas of the new multichannel electrode produce MUAP's which are less affected by needle movement, but the signals need to be digitally differenced to obtain similar time durations as the SFEMG MUAP's. Actual simultaneous multi-channel collections were not performed, but the technique looks promising.

The present decomposition scheme requires the operator to analyze the data, to assess its stationarity and initialize the templates. While it is good practice to check the data quality and the template initialization is not too difficult, it would be desirable if the decomposition scheme was more automatic. Reliably determining the number, of active motor units and a representative shape for each is a difficult task which as of yet has not been suitably accomplished. Future attempts in this area might involve similar analyses such as that proposed by Gath (1975) who used periodicities in the autocorrelation function of the EMG to determine the number of motor units active and studies of the EMG's power spectrum to determine their initial firing rates. Clustering analysis (Vogel and Wong 1979) might also be another method of determining the number of motor units active and obtaining representative template shapes.

7.3 Clinical Application of Procedure

The recording and data analysis in its present state does not meet the initial objective that it be clinically applicable. The assessment of data quality and template initialization is a task which could be readily performed by the experienced Electromyographer. The recording protocol and technique is no more difficult than other presently suggested, quantitative clinical EMG procedures. The time required for the analysis is therefore the major factor precluding the procedures regular clinical use. This objective can then be met if dedicated hardware systems which would substantially reduce the time required to perform the analysis can be utilized.

The accuracy of the results are sufficient to contribute a number of potentially useful clinical indicators. Stalberg and Thiele (1973), Prochazka et al (1973) and Freund et al (1973) all suggested that changes in motor unit firing variability might be used clinically to indicate abnormal muscle. The mean firing rate, firing rate variance and the coefficient of variation, the ratio of the standard deviation to the mean, at certain percentage levels of maximum voluntary contraction (%MVC), might all reflect useful diagnostic information. The trends of these parameters as functions of time might also be used to indicate muscle abnormalities. These parameters can be used to measure fatigue and the point at which significant fatigue is indicated would also be clinically useful. The independence of the firing of motor units or the existence of synchronization of motor unit firings would indicate clinical abnormality.

The morphological information obtained with this technique could be used, as presently proposed by Stalberg (1983). The macro MUP's area, shape and peak to peak voltages are all extracted.

The force protocols used, the parameters measured and the normal and expected ranges of the measured parameters all need to be determined and standardized if an evaluation of the clinical value of the temporal information is to be performed. Studies recording the signals of alternate muscles of normals and subjects with known pathologies need then be investigated to determine the usefulness of any proposed new parameters.

Studies performed with multi-electrodes can increase the size of the population of motor units studied. The multi-electrode can also possibly add motor unit territories and fibre conduction velocity estimates to aid in clinical diagnosis.

It is hoped that the recording and signal analysis procedure presented here or some alternate measurement technique, be developed to the point were it could be implemented in a clinical environment. This would allow a combination of both temporal and morphological parameters to be used to effectively aid in the assessment of the clinical state of the human neuromuscular system. To this end, suitable temporal parameters must be determined and their clinical value confirmed. Efficient and reliable methods of measuring these parameters must also be available. Further research into the decomposition and analysis of EMG signals is required for such a procedure to exist.

APPENDIX 1

MUAP DETECTION HARDWARE

A1.1 Introduction

The successful compression of needle recorded EMG data is dependent on the consistent detection of the occurrence of motor unit action potentials (MUAP's). The MUAP's must be detected each time they occur and at the same point during their time course. This is performed, as discussed in Section 3.3, by monitoring, in a parallel channel, the analog SFEMG signal's slope and amplitude. When both the measured slope and amplitude exceed preset thresholds, a pulse is created which is input to the LPS hardware and used to generate a compression request interrupt to the collection-compression routine (see Section 3.2 for more details). Slope and amplitude monitoring are also used to assess needle movement as outlined in sections 2.6 and 6.2.

The hardware circuitry used to perform the required signal monitoring, threshold production and output pulse creation is outlined in this appendix. Additional circuitry used to power the force transducer, amplify and filter the force transducer's bridge circuit output and to generate force target ranges is also described. A block diagram, Figure A1.1, depicting the various component circuits contained in the MUAP detection hardware is included.

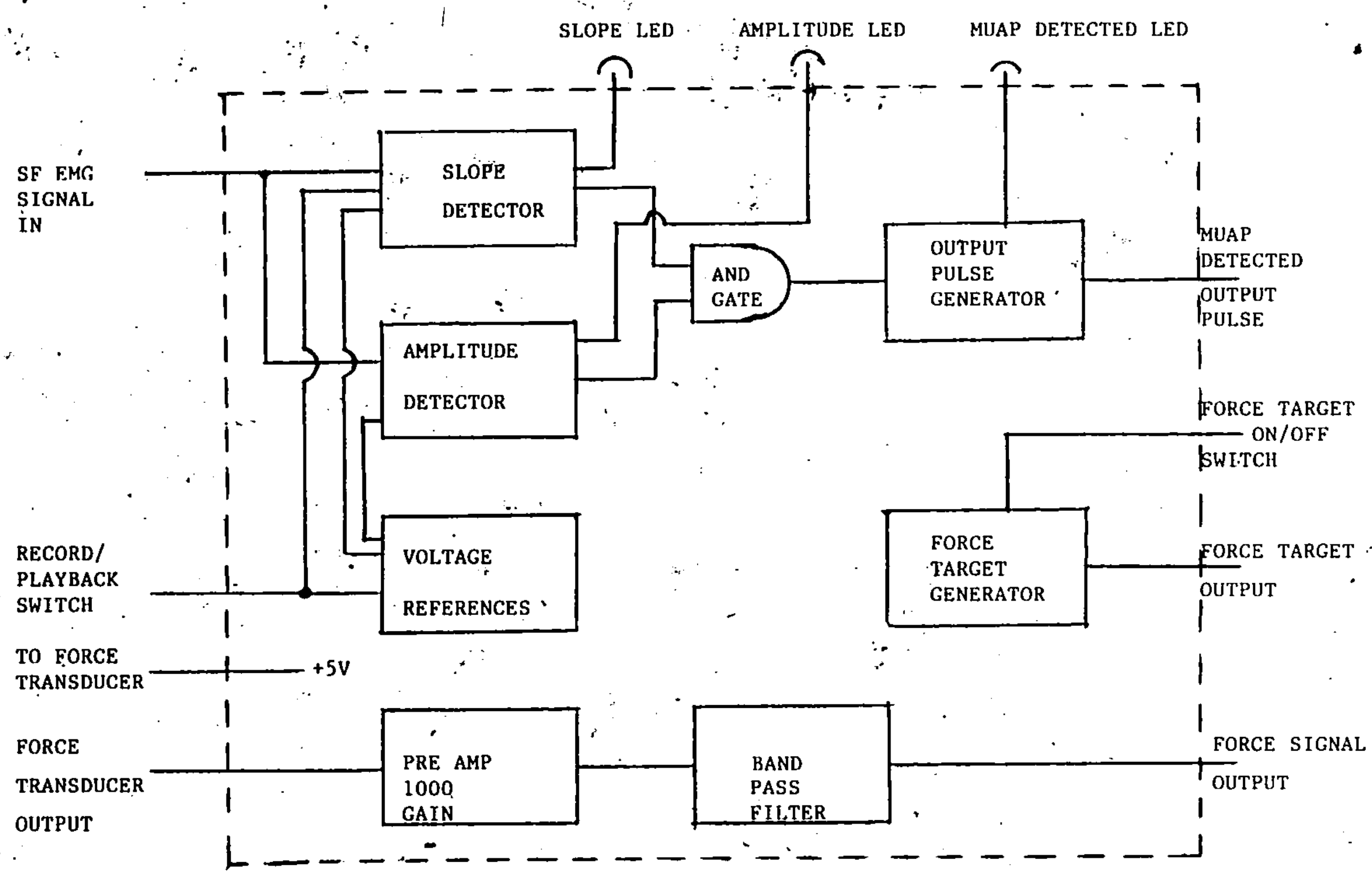


FIGURE A1.1
MUAP DETECTION HARDWARE BLOCK DIAGRAM

A1.2 Slope Monitoring

The measurement of the input signal's slope, the detection of the existence of sufficient slope in the monitored input signal and the consequent generation of a suitable output pulse is performed by the slope detection circuit. The slope detection circuit, shown in Figure A1.2, consists of a discrete component sample and hold circuit, a voltage comparator and an output pulse generator.

The sample and hold circuit consists of two operational amplifiers (op amps) on a single LM1458 chip, a dual retriggerable one shot 74LS123 chip operating as a logic signal generator and a single cell of a CD4066 bank of mosfet logic switches. One of the LM1458 op amps, the sample and hold op amp, has the DC uncoupled SFEMG input signal as one of its inputs. The other input is tied to ground through a resistor and the other LM1458 op amp connected as a buffer. This op amp will be called the buffer op amp. The SFEMG input signal is DC uncoupled by a series connected input capacitor and resistor. The output of the sample and hold circuit is the output of the sample and hold op amp.

Both sides of the 74LS123 are interconnected to perform as a bistable. Its output flipflops between being at 5 volts or at 0 volts. This output is used as the logic signal for the sample and hold circuit and is input to the gate of the mosfet switch used. When the logic signal is high, the input to the sample and hold op amp is tied to ground through the buffer op amp by the closing of the mosfet switch. The output of the sample and hold op amp is then driven to zero. When

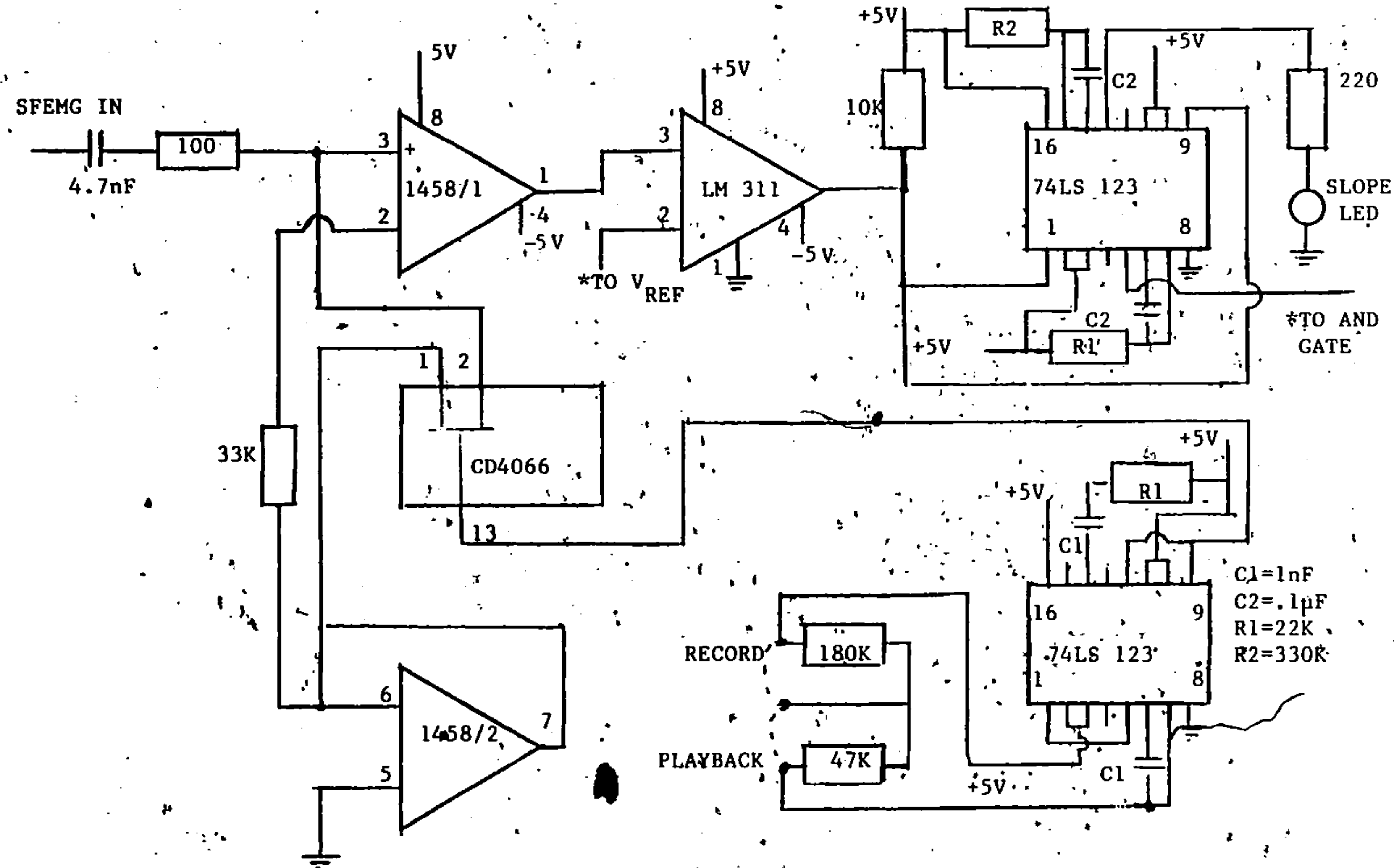


FIGURE A1.2
SLOPE DETECTION CIRCUIT

the logic signal is low, the mosfet switch opens and the sample and hold op amp input is connected to the DC uncoupled SFEMG input signal. The output then tracks the DC uncoupled SFEMG input signal. After a specified time, the sample and hold op amp inputs are again set to ground as the logic signal goes high.

The peak output (positive or negative) of the sample and hold circuit during the time its logic signal is low is proportional to the slope of the input signal. The proportionality constant is equal to the length of time the logic signal is low. If this time is suitably short, accurate estimates proportional to the input signal's slope are obtained.

The time duration for which the logic signal is low or high is determined by resistor capacitor pairs connected to each side of the 74LS132. The off time is set to .025 ms. The on time is set to .010 ms. The slope of the input signal is not monitored during the logic signal high state. The on time is therefore minimized to limit the amount of input signal not monitored.

Detecting if the measured input signal slope exceeds a certain selected slope threshold is accomplished by comparing the sample and hold output to a preset threshold. The threshold is equal to the slope to be exceeded multiplied by the time the logic signal is low and the gain of the input signal amplifier. The comparison is performed by an LM311 voltage comparator, with one input connected to the sample and hold output and the other input connected to an adjustable voltage threshold. If the sample and hold output exceeds the threshold, then the measured slope of the input signal has exceeded the threshold slope requirement. The off time being set at .025 ms and the input gain being 1000, requires a 25 mV threshold for each V/s slope to be measured. For example, to test for the exceeding of a 6 V/s slope, the required voltage threshold is set at 150 mV. The voltage threshold production and selection will be discussed later in this appendix.

A switch is provided which allows the slope selected to be exceeded to be divided by four by extending the off logic signal time by a factor of four, while the voltage threshold remains constant. This allows the recorded signal to be slowed down by a factor of four and still produce the same output pulses as the real time signal. The slowing down of the signal is performed by playing back the recorded data at a tape speed four times slower than the recorded speed. This is necessary because of real time sampling rate limitations of the collection-compression routine. The switch in the playback position assumes operation in the extended, by a factor of four, time base. The switch in the record position assumes real time operation.

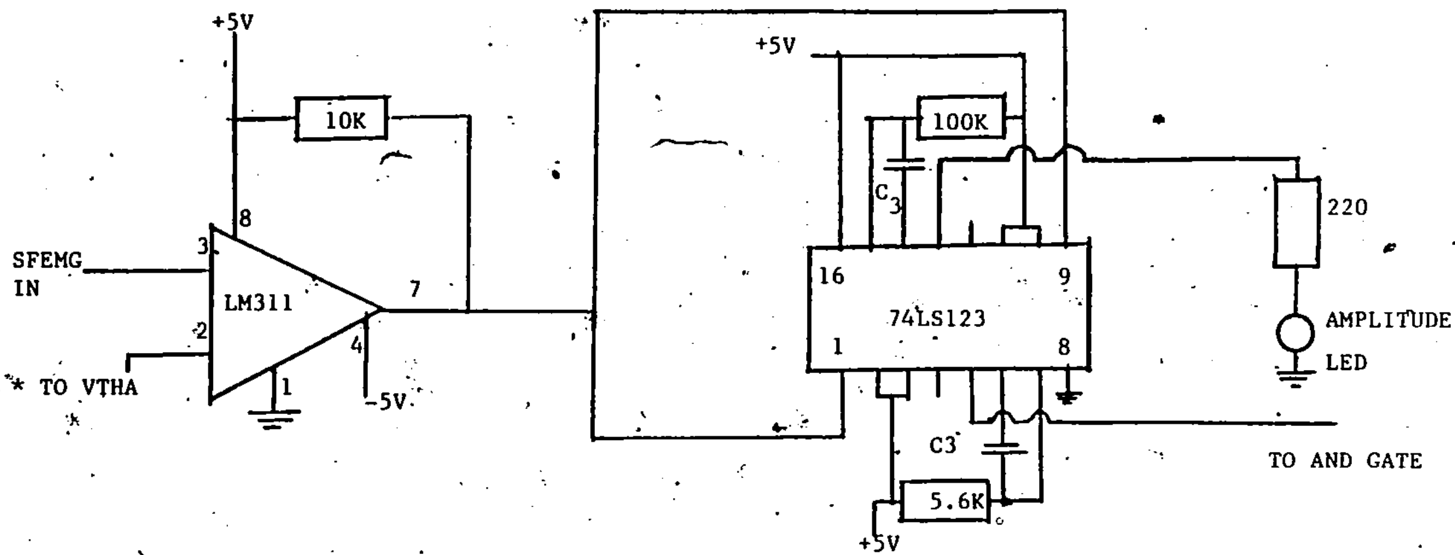
When the preset voltage threshold is exceeded, output pulses are created to indicate the existence in the input signal of a slope greater than the threshold slope. The output pulse generator is a 74LS123 dual retriggerable one shot. The changing of state of the voltage comparator, as the preset voltage threshold is exceeded, simultaneously triggers the generation of two separate 'slope threshold exceeded' output pulses. The length of the pulses are controlled by the resistor capacitor combinations connected to each side of the 74LS123. The width of the output pulses are set to .10 ms and 1.0 ms respectively. The shorter output pulse is fed to an and gate and the longer pulse to a light emitting diode (LED). The and gate is used with the amplitude detection circuit output to signal a MUAP detection. The LED provides a flashing light which signals the exceeding of the selected slope threshold. The pulse to the LED is lengthened to make the flashing LED more visible.

A1.3 Amplitude Monitoring

The detection of epochs when the voltage level of the input signal is above a preset level and the production of corresponding output pulses indicating this state is effected by the amplitude detection circuit. The amplitude detection circuit, shown in Figure A1.3, is composed of a voltage comparator and an output pulse generator.

The voltage comparison is performed by a voltage comparator chip. One input is the SFEMG input; the other is connected to a selectable voltage reference. The selection and production of the voltage reference will be discussed later in this appendix.

The output of the voltage comparator is connected to an output pulse generator similar to the one used in the slope detection circuit. When the voltage reference is exceeded, the output of the voltage comparator goes high causing 'amplitude threshold exceeded' output pulses to be created by this output pulse circuit. The lengths of these output pulses are controlled as in the slope detection circuit and are set to similar values. The shorter output pulse is fed to an and gate and the longer pulse to a separate LED. The and gate is used with the output of the slope detection circuit to trigger a MUAP detected pulse.



C3 = .22 μF
VTHA = AMPLITUDE VOLTAGE THRESHOLD

FIGURE A1.3
AMPLITUDE DETECTION CIRCUIT

The LED provides a flashing light indicating the epoch when the preset amplitude threshold is exceed.

A1.4 MUAP Detected Output Pulse

The production of the 'MUAP detected' output pulse is performed by the output pulse generation circuit which is composed of an and gate and a 74LS123 chip. The inputs to the and gate as stated above are the output pulses of the slope detection and amplitude detection circuits. The output of the and gate simultaneously drives the two sides of the 74LS123 chip. One side produces the 'MUAP detection' output pulse which has a .10 ms duration and is output to the computer. The other side produces a 1.0 ms duration pulse which is used to drive a separate LED to indicate that a MUAP has been detected. The 74LS123 chip is similarly connected as in the slope and amplitude detection circuits. The output pulse is not created unless both the slope and amplitude thresholds are exceeded simultaneously or at least within .10 ms of each other.

A1.5 Voltage Reference

The creation and selection of the required thresholds for the desired amplitude and slope measurements is performed by the voltage reference circuit. The voltage reference circuit consists of a 1.2 V LM113 voltage reference, suitably chosen 1% resistors and two eight position DIP selector switches. The LM113 voltage reference is series connected with a 4.7 Kohm resistor to the 5 V supply. The LM113 provides a stable 1.2 V voltage reference. This reference is then connected to one of eight selectable voltage divider legs, to produce the desired voltage reference, for the slope detection circuit. Similarly, the voltage reference is connected to one of eight selectable voltage divider legs to produce the desired voltage reference for the amplitude detection circuit. The voltage divider legs which are connected to the 1.2 V reference are determined by DIP selector switches. One eight position switch and eight different voltage divider legs are provided for each of the slope and amplitude detection circuits.

The voltage levels which are provided to select amplitude thresholds from are; .050, .100, .150, .200, .300, .400, 1.2 and 0 V. The last threshold is always exceeded and the MUAP's are detected on slope criteria alone. These voltage levels assume an input amplifier gain of 1000. The corresponding signal level thresholds are thus 1000 times less. The desired amplitude threshold is selected by turning on the appropriate amplitude DIP switch. No more than one amplitude DIP switch should be on at any one time.

The voltage levels which are available for slope threshold selection are; .025, .050, .075, .100, .125, .150, 1.2 and 0 V. Assuming a .025 ms slope measurement time and an input amplifier gain of 1000, these voltage levels correspond to the following slope thresholds; 1, 2, 3, 4, 5, 6, 48 and 0 V/s. The last threshold is always exceeded and the MUAP's detected by amplitude criteria only. The desired slope threshold is selected by turning on the appropriate slope DIP switch. No more than one slope DIP switch should be on at any one time.

A1.6 Force Processing Circuits

The remainder of this appendix will discuss circuits used for the measurement of the force produced during a contraction and the production of a force target range. The force produced during a contraction is measured as the amplified and low pass filtered output of a force transducer. The force target range is produced as the sum of the output of a triangular wave generator and a high frequency square wave of variable size and is controlled by an on/off switch. Figure A1.4 shows the force processing circuit schematically.

The force transducer is composed of four 120 ohm strain gauges connected in a full bridge circuit. The bridge is driven by a 5 V DC signal. The output of the bridge is amplified with a gain of 1000 using an Analog Devices AD521 precision instrumentation amplifier with offset trim to null the output for zero force production. The low pass filter is a fourth order Butterworth, implemented as an active voltage controlled voltage source circuit using two op amps on a LM1458 chip and the associated resistors and capacitors as outlined by Johnson et al (1980). The cutoff frequency is set at 10 Hz. The amplified and filtered force transducer output is available for display on an oscilloscope and input to a tape recorder channel, as shown in Figure 2.2. The experimental force measurement setup and restraining device is diagramed in Figure A1.5.

The force target range is generated using a 8038 function generator chip and a 74LS123 chip. A low frequency triangular wave output of pin 3 of the 8038 is added to a high frequency square wave

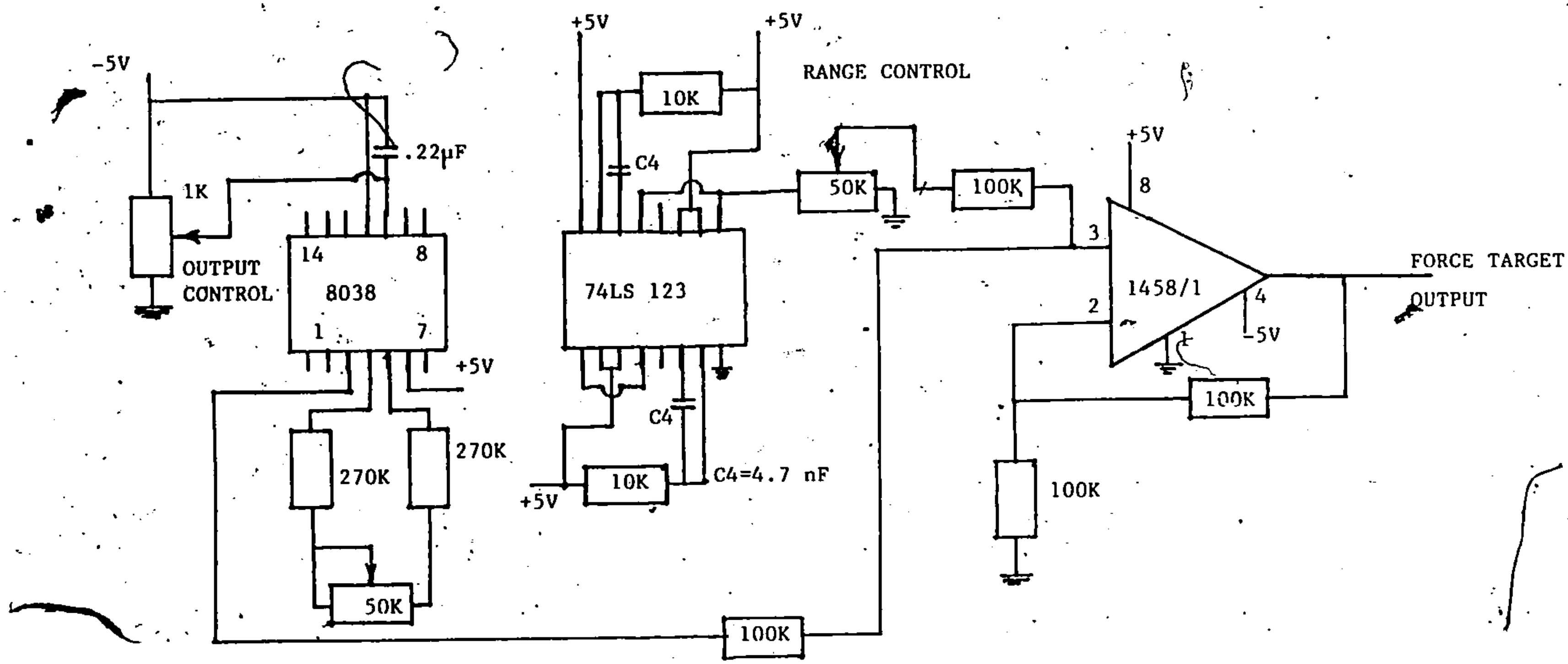


FIGURE A1.4
FORCE PROCESSING CIRCUIT

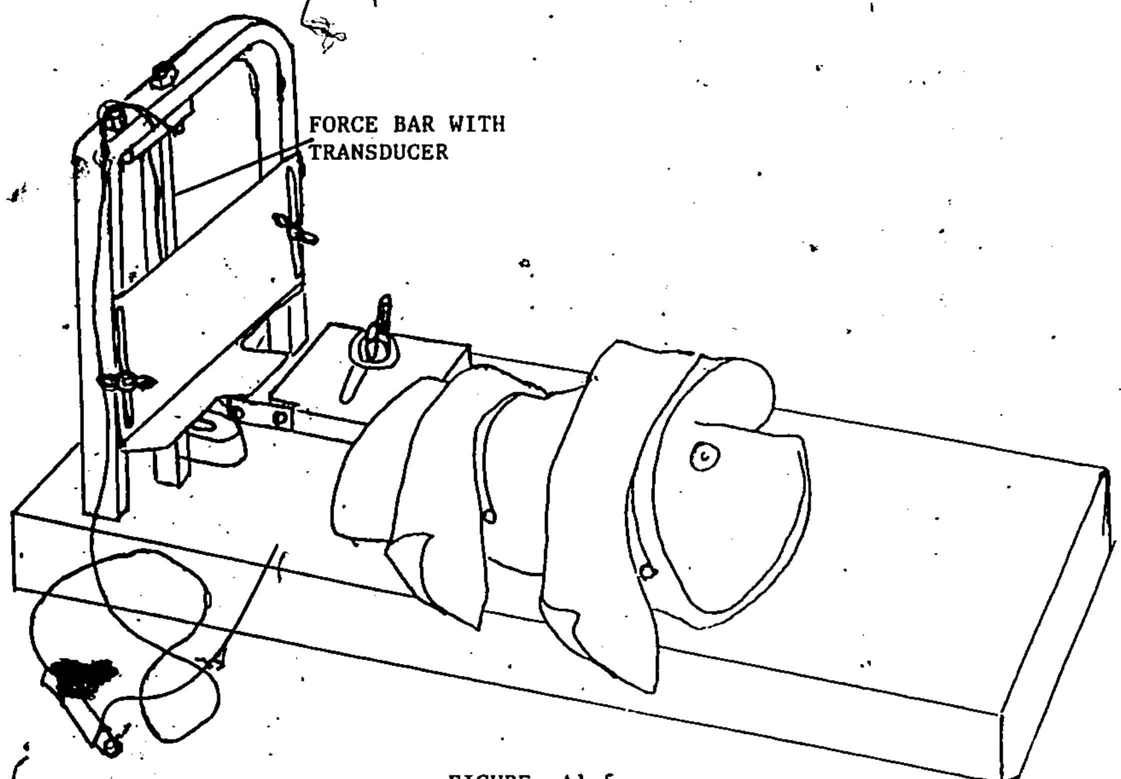


FIGURE A1.5
FORCE MEASUREMENT SET UP AND RESTRAINING DEVICE

signal, produced by the 74LS123 Chip to create a high frequency square wave with a slowly changing baseline. This signal, when fed to an oscilloscope, with a fast time sweep and no square wave triggering synch, reduces as slowly vertically sweeping shaded range on the oscilloscope screen. The shaded range displayed is produced by the nontriggered square wave. The vertical sweeping is provided by the slowly changing triangular wave. Together they produce a force target range in which the subject can be requested to maintain the force output signal.

The triangular wave is set to have a 30 second period by suitably selecting the charging capacitor and resistors. The charging and discharging resistances, those connected between pins 4 and 5 of the 8038 and the 5 V supply, are adjusted so that the triangular output has a 15 second up time and 15 second down time.

The square wave is produced, as is the logic signal for the sample and hold section of the slope detection circuit, using a 74LS123 dual retriggerable one shot. The duty cycle of the output is, however, set to 50% and the total period of the signal is .200 ms. The width of the range, the height of the output square wave, is controllable by adjusting a potentiometer connected across the output of the 74LS123 and ground.

The two outputs are added together using one half of a LM1458 chip connected as a summing amplifier. Each output is connected through an input resistor to the unity gain summing amplifier. The output of the summing amplifier is the sum of the input signals. The resulting sum is an adjustable force target range which vertically sweeps the oscilloscope screen every 30 seconds.

A switch is provided which shorts the charging capacitor through a series resistor. The force target range goes to the zero force output point on the oscilloscope screen with the switch in this position (off). With the switch in the 'on' position, the force target goes through its entire range starting at zero. The displayed force target range starting point (zero force output) and the sweep range are adjustable using the oscilloscope controls.

APPENDIX 2

DATA COLLECTION-COMPRESSION ALGORITHM

A2.1 Introduction

This appendix describes, in detail, the collection-compression algorithm of the program developed to store compressed data for the new recording protocol introduced in section 2.6. It explains the program states used to accomplish two channel continuous data collection, handle compression requests, perform the actual data compressions and final disc storage of the desired data.

A2.2 Data Collection

The sampling and digitization (sampling) of the data is performed by the LPS 12 bit A/D conversion hardware. This hardware is initialized to perform conversions in 2's offset format. The sampling of each active channel and transfer of the digitized result to the ring buffer is effected by a sampling interrupt service routine. The A/D done interrupt of the LPS system is used to initiate this sampling service routine.

The A/D done interrupt is created when an analog to digital conversion is completed by the LPS A/D circuitry. This interrupt is enabled during program initialization by setting the interrupt enable bit in the A/D control register. The A/D converter is also addressed to channel one, by setting the appropriate bits of the A/D control register, at this time. An A/D conversion is started when the LPS clock overflows. This is because the overflow enable bit of the A/D control register is set during the program start up sequence. The clock is counting in the repeated interval mode. Therefore, the command to sample and convert data in channel one is given at set intervals by he LS clock and the end of this conversion causes a program interrupt.

Upon entry into the sampling interrupt service routine, the completed result of the conversion of channel one is transferred to the ring buffer. The second channel is then sampled with a slight delay and the result is transferred to the ring buffer as well. Therefore, the two channels of data are transferred to the ring buffer in a nested format. A ring buffer pointer, which controls the location of the transfers to it, is incremented. If the ring buffer pointer is at the end of the buffer, a ring buffer counter is incremented and the pointer is directed to the beginning of the ring buffer. The ring buffer pointer along with the ring buffer counter are used to count the total number of samples that have been collected since the beginning of a collection-compression run. This number of samples count is used to represent elapsed time. Control is then returned to the interrupted point in the program.

The sampling rate is determined by the LP clock overflow frequency. With the clock counting in the repeated interval mode, this frequency is dependent on the initial count value and the count speed. Both of these values are set at the beginning of the program. The clock count speed is fixed at one MHz and the initial count is determined, based on the sampling rate chosen by the operator. The clock is started in this repeated interval mode whenever collection-compression is being performed. It is used in the external event timing mode for timing DMA writes, but it is then restarted in this mode when collection-compression resumes. It continues in this mode until program termination, when it is turned off.

For double channel collections, the sampling rate is the higher of the rates required to properly represent each of the data channels. However, a compression sampling rate lower than the collection sampling rate can be effected for the second data channel. This can be accomplished by selecting for compression, from the ring buffer, suitably spaced channel two samples with a fixed number of channel two samples between them. This is explained in more detail later in this appendix.

A2.3 Data Compression Requests

The detection of a MUAP, by the MUAP detection circuit, results in a program interrupt separate from the sampling interrupt. This interrupt is created by the Schmitt trigger of the LPS interface and is of lower priority than the sampling interrupt. The service routine for this interrupt first checks the number of samples that have been collected since the last occurrence of a MUAP. If the number of samples corresponds to at least the minimal time required between MUAP's, then the routine continues. If [illegible] time limit has not been met or exceeded, it is assumed that a supe[illegible] of two or more MUAP's has occurred or that the same MUAP has been detected twice. The service routine simply returns control to the point in the program which had been interrupted. The requirement for a minimal time interval between MUAP occurrences is solely to avoid multiple compressions of the same MUAP, which can occur with complex MUAP shapes. This time interval is input by the operator and is less than the time duration of a compression epoch.

If the MUAP time interval constraint has been satisfied, the service routine continues. It loads the present value of the ring buffer pointer into the top of the compression request stack and moves the top of the compression request stack down in memory. The time of the interrupt, as represented by the value of the ring buffer counter and the ring buffer pointer, is transferred to the time buffer. The service routine then returns control to the interrupted point in the program.

A2.4 Data Compression

The actual compression of data is performed in the absence of interrupts. If the compression request stack is not empty, a request for compression exists. The bottom value in the compression request stack is then moved into a compression range pointer which defines the center of a compression range for data channel one. The bottom of the compression request stack is then moved down in memory. The extent of the compression range for each channel is dependent on the number of channels being compressed and the number of samples per MUAP being compressed. The compression range for the second channel also depends on the ratio of the collection and compression sampling rates. The number of samples compressed for each MUAP is determined by the time duration desired for the representation of the MUAP and the compression sampling rate. This parameter is input by the operator during program initialization. The number of samples compressed is the higher of the values required to properly represent the shapes as seen in each data channel. The operator can choose between 25, 50 or 100 samples being compressed per MUAP.

The data in the ring buffer is transferred into the compression buffer one sample and channel at a time. The nested data for double channel collections remains nested in the compression buffer. The transfers are controlled by compression pointers, one for each channel. The compression pointers are calculated by subtracting offsets from the compression range pointer. The offset for channel one is determined as the number of samples to be compressed for each MUAP, times the number of channels being collected. The offset for channel two is similar to the offset for channel one, but for an additional multiplication by the ratio of the collection to compression sampling rates for channel two and a subtraction of two for the channel to channel offset in the ring buffer. These offsets are computed during program initialization. The value of the compression pointer, for each channel, at the beginning of a compression epoch is then determined by subtracting, from the compression range pointer, the offset calculated for each channel. The compression pointers are incremented after each transfer. The increment used for each compression pointer is the number of channels being collected, times the ratio of the collection and compression sampling rate, times two. The final multiplication is to convert the increment from words to bytes, since the PDP-11 is byte addressable. The ratio for channel one is always one. A value other than one, for the ratio for channel two, will result in a reduced compression sampling rate for channel two. The transfers and pointer incrementing continues until the required number of samples has been moved. Compression is not started if for each channel the ring buffer pointer is not a full compression range ahead of the intial value of the compression pointer. The program enters a wait state until this condition is met. A detailed schematic of the collection-compression data structure is included in Figure A2.1.

If a MUAP occurs during a compression sequence, the compression is simply interrupted, the current ring buffer pointer value is put on the top of the stack and the top of the stack is moved down in memory; the elapse time is placed in the timing buffer and the program returns to its original point in the compression sequence. A corresponding sequence of events is followed when a sampling interrupt is serviced during a compression epoch. If the compression request stack is emptied, the top of compression request stack is moved back to its original place in memory and the program enters a wait state. The compression range pointer marks the center of the compression range and the compression actually starts with samples collected earlier in time. The amount earlier is dependent on the maximum compression range of the active channels. Therefore, the collection process must have been active for at least this time to make these samples available. MUAP's occurring before this time are therefore not compressed. The MUAP detection service routine, is not used until a sufficient number of

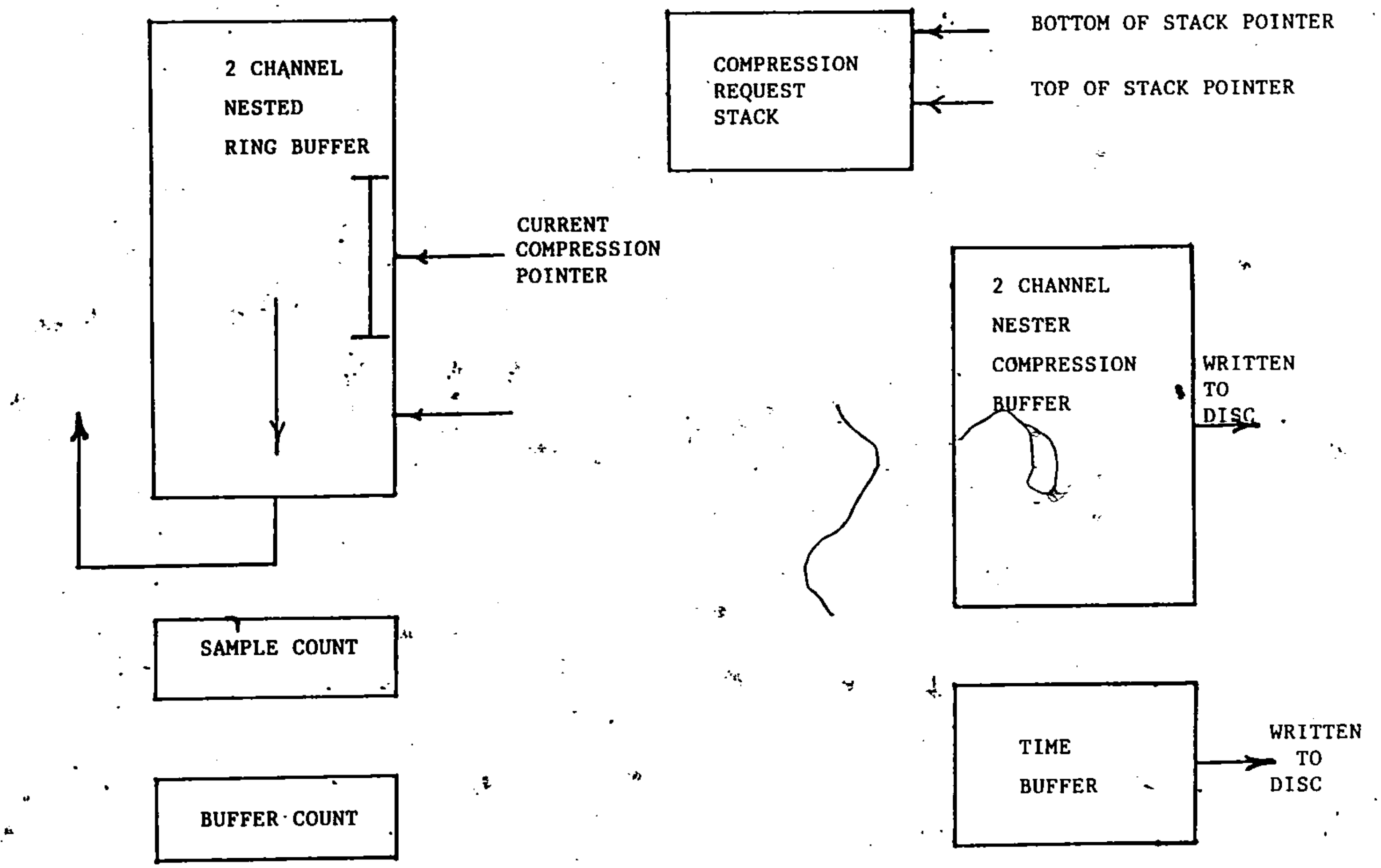


FIGURE A2.1

COLLECTION - COMPRESSION DATA STRUCTURE

samples have been collected. An initial interrupt service routine is used to check this and transfer future interrupt control to the MUAP detection service routine when a sufficient number of samples have been collected.

A2.5 Disc Storage

The compression buffer, when full, is written to disc by DMA. MUAP's occurring just previous to this or during this time are lost. The collection, consequently, is not continuous. It is subdivided into time intervals, which are based on the frequency of MUAP occurrences, the number of samples collected to represent the MUAP, the number of channels compressed and the length of the compression buffer. Nevertheless, a fixed number of MUAP's are compressed each time. This fact is used by later programs in calculating motor unit firing rates. The elapsed time is calculated continuously, however. The LPS clock is started in the external event timing mode at the beginning of the execution of this state and is stopped at its completion. The time spent in this state is converted to a number of samples count and appropriately added to the ring buffer counter and the ring buffer pointer.

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