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Project Brief**

**Project Title:  
Diagnosis of neuromuscular disease using  
surface EMG with neural network analysis.**

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# **Diagnosis of neuromuscular disease using surface EMG with neural network analysis.**

## **Description of the problem domain**

Neuromuscular diseases effect the structure of nerve and muscle cells. Many are degenerative and certain conditions can cause complete immobilisation as well as being potentially fatal. Different conditions affect different muscle groups. An example is Duchenne Muscular Dystrophy. It is a genetically determined disease that affects the body's ability to produce an enzyme, *kinase*. This enzyme allows muscle cells to burn up energy, without it, the cells cannot burn the energy and therefore cannot contract. The disease affects children and is degenerative. If untreated, as the child ages their mobility decreases as more and more muscle fibres are effected. Eventually the child is totally immobilised. Eventually the muscle cells of the heart and lungs are effected leading to fatalities. Most sufferers of Duchenne die in their early twenties. There is currently no cure.

Early diagnosis is important for two reasons. Firstly, it allows the patient to build up their muscles before the onset of degeneration, thus extending the amount of time that they have mobility. Secondly, the careful prescription of drugs can slow the degeneration. It is therefore important to devise accurate methods of diagnosis. Currently, methods of diagnosis include any or all of the following: assessing the patients history, blood tests and muscle biopsies. The latter two methods, whilst being relatively accurate, may take weeks to obtain a result. Another commonly used method is electromyography [2].

## **Electromyography**

Muscle is made up of many muscle fibers, groups of fibers are connected to a nerve cell called a spinal anterior cell.

Voluntary contraction of a muscle creates an action potential in *spinal anterior horn* nerve cells. Each spinal anterior horn cell is connected to a group of muscle fibers, together this is known as a *motor unit*. The action potential then causes a depolarization and a subsequent twitch in the muscle fibers connected to each nerve cell. The synchronized twitching of many muscle fibers causes the desired macroscopic movement. The depolarization of each muscle fiber membrane creates an electrical signal. The resulting signal generated by this group of cells is referred to as a *motor unit action potential* (MUAP) [2] [6].

The changes brought about by a particular disease alter the properties of the muscle and nerve cells, thus causing characteristic changes in the MUAPs. An intramuscular electrode and a differential amplifier can be used to measure MUAPs. Measuring this electrical signal is called electromyography (EMG).

Trained clinicians are able to use a patient's EMG signal as an aid in the diagnostic process due to the characteristic changes of the MUAPs. Assessing the signal visually and statistically provides the Doctor with information about the type of disease and the stage of progression

As a primary guide clinicians use their knowledge and experience of different conditions with a visual appraisal of an EMG signal. An example of this is that a particular EMG may have a few large spikes within it. Taken in isolation this information is not very helpful. However when combined with the patients age the signal becomes an aid to diagnosis. Rogue peaks much greater than the others in the EMG are regarded as a normal condition for an elderly patient. The random peaks are a symptom not of a disorder but simply of old age. However, the same signal if seen in a child would indicate that something was wrong [25]. Another example, myopathies (diseases of the muscle) are generally characterised by small, rapidly firing MUAPs. [2],[25] Another example is the appearance of 'doublets' as seen in motor-neurone disease. In this instance a motor unit discharges twice each time it fires as can be seen in the figure1. below.

**Figure 1. An EMG signal. Vertical axis is 1 mV, horizontal represents 1s Note the occurrence of twin peaks, indicating the motor unit discharging twice in quick succession, indicating Motor Neurone Disease.**

A more recent development has been the quantitative analysis of the signal. By applying statistical measures to the signal, such as the number of turns the signal makes i.e. changing from a positive gradient to a negative gradient a more empirical approach was instigated.

Beginning with Willisons [24] investigation of the relationship between the number of turns and amplitude and continuing with Stalbergs 'cloud' [16], a plot of mean amplitude against turns/frequency, the quantitative approach has become a clinical tool in EMG practice. A large amount of work has been carried out on studying quantitative measures of EMG signals[2].

The EMG technique is a much studied and well-utilised diagnostic clinical tool. Its advantage is that it can give very accurate results much quicker than blood tests and biopsies, which take significantly longer.

There are drawbacks however. These are largely related to the invasive nature of the technique.

- The technique requires that a needle electrode is inserted into a semi-contracted muscle. This is in order to reduce the movement of the electrode within the muscle during the next stage. The patient then has to fully contract the muscle. Full contraction is used to provide an easy to replicate benchmark. The exerted force may change over time but this in itself is an indication of the health of the muscle. This procedure presents specific problems. Not least of which is that the whole procedure is unpleasant for the patient. It can be difficult for the Doctor, especially when dealing with the very young or old as they lack the requisite motor control [2],[26].
- Many neuromuscular disorders are degenerative. In order to assess the degeneration repeat tests must be made. To preserve consistency the same area of the same muscle should be used. This is impractical because the physical damage caused by the electrode leads to scarring. This prevents that position from being used again in tests[2],[26].
- The needle electrode only measures the electrical activity of the few adjacent cells. This is a problem in that certain conditions are 'patchy' in their effect on a particular muscle. Multiple tests must therefore be performed in order to get a good idea of the condition of the whole muscle. The issues of unpleasantness and scarring are relevant here[2],[26].
- Great skill is needed on the part of the clinician to place the electrode in a position within the muscle that causes a good signal. This can be time consuming and again unpleasant for the patient as the electrode is manipulated within the muscle whilst the Doctor listens to the signal through a loud speaker. When the sound is 'crisp' the electrode is in a good position to record an accurate EMG [2],[26].
- The knowledge and skill of the clinician require a great deal of time and effort to acquire.

### ***Aim***

The aim of this project is to investigate the potential of a non-invasive clinical system capable of diagnosing a range of neuromuscular diseases. An overriding priority is that the system causes the minimum distress to the patient. A second priority is that use of the system requires the minimum amount of both the patient and Doctors' time in order to perform its evaluation..

### ***Choice of approach***

A significant concern for both patient and Doctor is the need to insert intramuscular electrodes. The first stage of this report is therefore to find a non-invasive method of recording electrical activity of the muscle.

Fortunately there is a fairly well understood method already available. There is a body of knowledge concerning the use of *surface* EMG (sEMG) techniques [7]. The procedure is the very similar to that used for EMG except for the electrode. Instead of a long needle like device inserted into the muscle a flat electrode can be placed on to the skin. This non-invasive method negates many of the problems associated with traditional EMG techniques outlined above.

### Advantages of sEMG

- There is significantly less discomfort,
- There is no tissue damage and therefore no subsequent tissue scarring. This allows for unlimited repetition of tests in exactly the same place
- The obtained signal is taken from a much larger area of the muscle thus avoiding the problems caused by 'patchy' conditions.
- For the above reason, there is a reduced need for precise positioning. This leads to a decrease in the time taken to perform the procedure.

There is however a significant problem with the sEMG method. The analysis of the subsequent signal has been virtually impossible to analyse [7].

### Disadvantages of sEMG

- The signal is greatly attenuated, due to the greater distance between source and electrode, plus the barrier presented by the skin and subcutaneous fat layer. EMG signals are measured in mV, sEMG signals are measured in  $\mu\text{V}$ . There is great potential for noise to corrupt the signal thereby reducing the signal-to- noise ratio.
- The presence of the skin and fat layer causes frequency degradation. Typical EMG signals contain frequency components up to 1000Hz. Signals taken from the skin surface only contain components up to the 300 Hz region.
- The RMS power of an EMG is at approximately 50-60 Hz. This is the same frequency range as the power supply and the electrocardiogram signal produced by the heart muscle. These factors can introduce considerable artefact to the signal.
- The signal is produced by a *much* greater number of motor units than that recorded by EMG. The resulting interference pattern is therefore much more complicated.

The above factors combine to obliterate the patterns and structures commonly found within an EMG

signal. This makes it useless for clinicians to diagnose conditions with current techniques using sEMG. For this reason, the sEMG technique has been largely neglected by the medical profession. There has however been a sizeable body of research investigating the relationship between exerted force and sEMG,[15][18][7] but little research into using sEMG as a tool for directly diagnosing disorders [21].

It was decided to apply recent advances in neural network technology to the signal analysis stage of the problem.

## ***Method***

There will be several distinct phases to the method, Data Acquisition, Data Pre-processing and Data Analysis.

### **Data acquisition**

The first on-going phase is data acquisition. This is possible thanks to the generous co-operation of Dr. Wimalaratna, a consultant Electro-physiologist at Derriford Hospital in Plymouth. He has kindly agreed to provide sEMG data taken from patients he sees in his clinic. Patient confidentiality will of course be preserved. Due to the signal degradation caused by the subcutaneous fat layer the particular muscle to be sampled is to be carefully selected for this trial. Although different conditions can affect different muscle groups it is intended for this study to use the Tibialis Anterior muscle. The reasoning for this is that it has been shown to be unaffected by the patient's weight, even obese individuals still provide a good signal from this muscle. The signals will be recorded using a medically proven instrument, (the Nicolet Viking IV). This rather expensive piece of equipment is in daily diagnostic service and is known to provide signals with very little noise. Use of a differential amplifier as close to the electrode as possible will remove common noise such as that caused by the heart and reduce transmission losses. The signal data will be in the form of a time-series of voltage values. The data will be stored in MS Backup format onto the machine's integral hard disk. This data will be regularly downloaded to floppy disk to be analysed at the University.

A potential problem could be created by only being able to sample a small number of patients. A similar difficulty could be encountered in sampling healthy individuals, there may be issues involving the use of an NHS machine to test healthy people. These problems could lead to a small or biased data set. In this event there may not be adequate data to successfully train a network. This issue will be discussed further in the Data Pre-processing section below. A second potential problem could be that patients seeing the consultant are there in order to diagnose a condition. Current techniques do not provide an instant diagnosis. Therefore there could be a considerable time delay between receiving the signal data and receiving a diagnosis. This issue will be discussed further in the Data Analysis section below.

## Data pre-processing

The initial phase is to convert from the MS Backup format used by the Nicolet Viking IV to a more suitable format for analysis. If the data set is small or biased there may be a need to ‘manufacture’ new signals. This can be achieved by adding a carefully selected level of noise to the collected signals [7]. It may prove to be a question of trial and error to find the correct level. In this way the data set can be increased with a minimal risk of creating false negative responses. It is possible to present the raw data values to a network with a very large number of input nodes. This approach would prove infeasible however as the size of the network would require very long training times. There would also be an air of suspicion of a large ‘black box’ that diagnoses conditions without explanation of how it did it. It is therefore more viable to take the quantitative approach as applied to EMG analysis. By observing a small number of features that are known to represent underlying physiology the input layer is reduced and the system gains medical credibility. The next phase therefore will consist of calculating the features to create a characteristic profile of each sEMG signal. It is intended that the careful selection of the features will provide enough information to create profiles to be characteristic of each. The choice of features is therefore a significant task within this project. The following section examines the feature selection in some depth.

### Features that characterise an sEMG signal:

There is significantly less knowledge of clinical use of surface EMG than that for EMG. Fortunately, the majority of the theories underlying EMG analysis are still valid with sEMG. It is possible therefore, to take the techniques used to assess EMG and apply them to sEMG. The following section is taken from [7]

There are four primary approaches to analysing the sEMG signal. Details about the patient, measures based on the raw sEMG signal, measures based on signal amplitude and measures based on frequency of the signal. Different muscles in the body generate different normal parameters for the measures. Therefore, it is important that the signal be obtained from the same muscle for every test.

#### Patient Details

- Age. Details about the patients age are of particular importance, as described in the introductory sections, a feature considered normal in an elderly person may be considered abnormal for a young person. Age may also help differentiate between different body sizes.
- Sex. The patients sex may also help determine affects caused by different body sizes.
- Weight. Taking weight into account may give some guide as to the affect of the subcutaneous fat layer.

#### Raw signal

Certain measures can be calculated directly from the signal:

- $V_{tt}$ . Mean value of peak-to-peak amplitude.
- $N_p$ . No. peaks in a given period of time (usually 1S).
- $N_z$ . A count of the number of zero-crossings per second.
- $N_t$ . The number of turns in a given period of time. A turn is defined as a change in direction of the signal above a given threshold value.

These measures depend largely on the selection of an accurate noise level. Studies show a noise level of between 100 -120  $\mu$ V (i.e. most of the signal) to be effective

**Amplitude:**

The method involves sampling the signal, recording the amplitude at those sampling points and constructing a histogram of the amplitudes and the number of occurrences of each, (see figure 2. below)

**Figure 2. A typical amplitude histogram from a healthy individual. Note the Gaussian distribution..**

This histogram gives rise to a probability density function (PDF) which can then be subjected to statistical analysis. The PDF of a healthy individual has approximate Gaussian distribution and a mean value of zero. This means that the curve can be described simply by its Standard Deviation (SD).

Certain disorders cause this curve to deviate from the Gaussian distribution. By calculating the statistical measures of skewness and kurtosis, these deviations can be largely characterised. Skewness (Skew) describes the asymmetry of the curve. Kurtosis (Kurt) is a measure that is particularly sensitive to activity in the tails of the curve. This relates to sEMGs dominated by peaks, these are characteristic of certain disorders.

The integration of the signal (IEMG), i.e. the area under the curve has been shown to have a linear relation with the exerted force.

Time / frequency:

By calculating the Fourier transform of the covariance function a power density function or frequency spectrum is obtained. A typical spectrum of a healthy M. biceps brachii. is shown in figure 3. below.

**Figure 3. Frequency spectrum of a healthy individual.**

Unlike the amplitude histogram, this curve cannot be characterised by a single measure like SD. Measures that have been studied include.

- $F_f$ . Frequency of the first peak. This is thought to be related to the mean firing frequency of the active motor units. This peak should not move when the exerted force is increased
- $F_{max}$ . Frequency of the highest peak i.e. the frequency that carries maximum power. Related to the geometry of the motor units and the dispersion of the motor endplate zone.
- $F_{med}$ . Median frequency. The frequency that divides the spectrum into parts of equal power. This has been shown to shift down as fatigue increases. Therefore contractions of a short duration (e.g. 2 seconds) need to be sustained
- $F_{-6dB}$ ,  $F_{-10dB}$ . Frequencies at which the spectrum is 6dB and 10dB respectively, below the peak. These values describe the tail of the spectrum, which is presumed to be related to the polyphasic nature of the MUAPS i.e. how well synchronised the muscle fiber firings are.

- $P_{-6dB}$ ,  $P_{-10dB}$ . Relative power of the spectrum above the -6db and -10dB frequencies. again related to the polyphasic nature of the MUAPS
- $P_{r100}$ . Relative power in the spectrum above 100Hz. Depends on the polyphasic nature of the MUAPS and the position of the spectrum.

## Use of these measures to characterise a disorder.

In tests of these measures on healthy non-healthy subjects, the following analysis was obtained.

The first peak ( $F_p$ ) is not always present with certain conditions, e.g. hemiplegia

Frequency of maximum power ( $F_{max}$ ) only really deviates from the norm with disorders related to giant MUAPs or decrease in conduction velocity of muscle fibres.

Median frequency ( $F_{med}$ ) is very sensitive to changes in conduction velocity. The parameter is also related to synchronisation of MUAPs, it will decrease as synchronisation increases. The deviation of ( $F_{10dB}$ ) frequency is seen in conditions of peripheral nerve lesions. The amount of force exerted during contraction may be a good guide as to the condition of the patient. The integration of the signal (IEMG) has been shown to be related to the exerted force and would thus serve as a means of gauging the force, useful in that this study does not intend to actually measure force directly during data acquisition. The other parameters tend to remain at the same levels regardless of force exerted.

There are out-of sample variations of many of these parameters. That is no two people will have exactly the same values for these measures. However, within-sample variation is much less. The measures especially those related to amplitude seem to be very reproducible over time for an individual.

The measures of median frequency ( $F_{med}$ ) and ( $F_{-10dB}$ ) are very reproducible across out-of-sample (i.e. different subjects). Hopefully this will be an important discriminant between conditions.

## Summary

The measures that will be used for this study are:

- *Patients details*
  - Age
  - Weight
  - Sex
- *Raw Signal*

- $V_{tt}$ . Mean value of peak-to-peak amplitude.
  - $N_p$ . No. peaks in a given period of time.
  - $N_z$ . A count of the number of zero-crossings per second.
  - $N_t$ . The number of turns in a given period of time.
  - IEMG. Integration of signal
- *Probability Density Function of Amplitude :*
    - SD. Standard Deviation
    - Skew. Skewness
    - Kurt. Kurtosis
- *Frequency spectrum*
    - $F_f$ . Frequency of the first peak
    - $F_{max}$ . Frequency of the highest peak
    - $F_{med}$ . Median frequency
    - $F_{-6dB}, F_{-10dB}$ . Frequencies at which the spectrum is 6dB and 10dB below the peak
    - $P_{-6dB}, P_{-10dB}$ . Relative power of the spectrum above the -6db and -10dB frequencies
    - $P_{r100}$ . Relative power in the spectrum above 100Hz

In summary, the features that are to be used are simply numerical values that describe the characteristics of the sEMG signal. These characteristics are intended to reflect the condition of the tested muscle. It hoped that the muscle physiology indicated by the measures would lead to the profiles forming discreet clusters in feature space for different conditions.

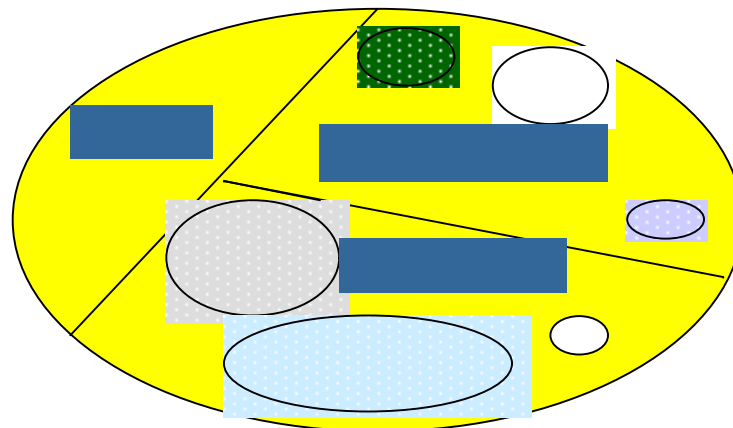
## Data Analysis

### What classification is required?

The combination of the measures discussed above will provide a profile of the sEMG signal. The profile will then be used to train and test the neural network that will be the core of the system. The network will analyse the input to provide the clinician with an accurate guide as to the underlying condition. The system will need to make very clear those cases that may be borderline, with a tendency to indicate false positives rather than false negatives where a positive is an indication of a disease. The output should ideally be some sort of map visually showing the relation between the case in question the sum of knowledge of other conditions. Statistical methods within medicine are quite rigorous. A significance of  $p < 0.005$  is required in order to be taken as a credible method. This relates to an classification accuracy of better than 99.5% correct.

This will be accomplished in three stages, see figure 4. below for schematic.

- The first stage is to simply differentiate between signals taken from healthy and diseased patients. This in itself is useful as it would remove the need for unnecessary insertion of electrodes into healthy people
- There are significant differences in the characteristics and treatment of disorders of muscle cells (myopathy) and nerve cells (neuropathy). The second stage is therefore to differentiate between neuro-disorders and muscular disorders. This would be a significant milestone as it this task has been shown to be very difficult using sEMG signals [21].
- The third and final phase is to be able to automatically differentiate specific conditions given a single sEMG profile. This task has never been achieved using EMG signals let alone the much degraded sEMG signal. If this task is accomplished this study will have achieved a *very* significant medical result.



**Figure 4. Schematic showing set of all possible conditions for a particular muscle. The set is segmented into several regions *healthy, neuropathy, myopathy* and *specific disorders* represented by the smaller elipsoids.**

### Choice of network

There are many possible types of neural network available to analyse the signal profiles. The options are discussed below.

- Multilayer perceptron (MLP)– the classic neural network, has been much studied and used in many diverse fields. MLP is included mostly as a benchmark by which to judge the other methods. The advantages of the MLP are that it is very good at mapping input to output data. The drawbacks are that it takes a considerable time to learn thus creating practical difficulties; the algorithm is

supervised, i.e. the desired output is used to train the network. This means that the network can only be trained once diagnosis has been made, again presenting practical difficulties. However by the end of the data collection period there should be enough complete sets of data ( i.e. sEMG signals and accompanying diagnosis) to train an MLP. Another drawback is the output. There is little potential for providing a visual display of the networks 'diagnosis' other than simple plots of values of output nodes. This may require further analysis on the part of the clinician in order to diagnose..

- Self-Organising Maps(SOM) – based on the Kohonen [10] network, SOM algorithms are unsupervised and can provide a visual representation of how the information stored within the network is organised. SOM algorithms are not as accurate as MLP when confronted with complex clustering in feature space.

Related to the SOM is the Learning Vector Quantization algorithm (LVQ) [10]. This is effectively an add on to the SOM. It is effectively another layer, on top of the SOM that allows an accurate classification of the SOM activity. The LVQ is a supervised algorithm, it would therefore require the complete data set to be trained. The algorithm can learn very quickly.

Combining SOM and LVQ can provide an on going training, as sEMG data comes in, with accurate analysis of the SOM by the LVQ when diagnosis become available.

- Fuzzy ART and fuzzy ARTMAP [26] are another combination of algorithms with a similar relationship as SOM and LVQ. Fuzzy ARTMAP is an unsupervised algorithm that has been shown to effectively classify clusters in feature space, similar to SOM. Fuzzy ART is a supervised algorithm and is similar to LVQ in that it examines the activity of the ARTMAP to provide an accurate classification of the input signal.
- A recently created algorithm [20], originally designed to classify feature space created by signal profiles from multi-sensor arrays or Electronic noses as they are commonly known would prove very useful for this problem. It has been designed to specifically counteract problems created by unusual shaped cluster in feature space. It is not known at this time if the clustering will be particularly unusual, however it is a potential pitfall, use of this new algorithm will reduce the potential errors.

The intention is to simultaneously train all of the above networks, in order to investigate the most suitable approach for further work.

As the data set increases the networks will need to accommodate the extra knowledge. The issue of expansion is overcome by acknowledging that accuracy is more important than time taken to train a network, therefore if a network needs to be improved by more training then so be it regardless of the time taken. This may cause practical problems. But this will be taken into consideration in the planning

stage, see Gantt chart in appendix.

## **SUMMARY**

This project intends to record clinically accurate data, taken from a wide range of individuals in varying states of health. The data acquisition will use the least distressing methods i.e. non-invasive surface EMG. Analysis of the data is intended to provide an automatic diagnosis of an individual's muscle condition. Success in this task would be a significant medical breakthrough. The study may well prompt a revival of interest in the sEMG technique, perhaps leading to a new clinical diagnostic procedure. The improved procedure could reduce patient distress and increase the speed with which diagnosis could be performed, thus impacting significantly on the effectiveness of a health service.

Variations of the technology could have many applications including physiotherapy, sports medicine and veterinarian applications ranging from assessing racehorse fitness to grading beef cattle. A full working system would have *significant* commercial potential.

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