Signal Processing for Electromyography Parameter Estimation

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Abstract: - Electromyography has been a key element in revolutionizing biomedical engineering. It has aided in the detection and treatment of patients with abnormal muscle movement. Further growth in this field is the development of a prosthetic or other assistive device to enable people to mobilize as they would be able to without their muscular difficulties. These devices need estimation of natural or healthy motion in order to effectively assist the patient. Signal processing for parameter estimation provides a path to modeling the healthy range of motion that must be replicated.

Key-Words: - electromyography, EMG, signal processing, parameter estimation

1 Introduction

Electromyography (EMG) is a technique for evaluating and recording the electrical activity produced by the muscular system. EMG is performed using an electronic instrument called an electromyograph. The electromyograph measures the minute electrical signals created by the flexing and movement of muscles, i.e., by detecting the electrical potential generated by muscle cells when these cells are electrically or neurologically activated, and produces a record called an electromyogram. The recorded electrical signals can be viewed, interpreted, and processed to determine activation level or recruitment order, to detect medical abnormalities, or to analyze the function of human or animal movement.

Signal processing techniques such as the Short-Time Fourier Transform (STFT) and wavelet transforms can be used for modelling EMG processes and parameter estimation for control system design. The models and parameters are utilized by the control system to determine the general diagnosis of the user.

Electromyogram results are used for diagnosing muscular diseases, including neuropathies and myopathies. Neuropathy is any disease that damages the nerves present in and around the muscles. Neuropathic disease has some defining EMG characteristics. One factor is a muscle signal whose action-potential amplitude is twice that of a normal muscle signal. This is due to the increased number of fibers-per-motor-unit because of the compensation for dead or damaged fibers. This compensation is called reinnervation. Another factor is an increase in duration of the action potential, which decreases the frequency of the overall signal.

Myopathy is any disease that causes damage to the muscle fibers. Myopathic diseases also have a few defining EMG characteristics, most notable are decreases in duration and area-to-amplitude ratio of the action potential. Patients with myopathy have a decrease in the number of motor units in the muscle.

Figure 1 shows three examples of EMG signals: 1) a healthy patient, 2) a patient with neuropathy, and 3) a patient with myopathy. The test point for all subjects was the same; the tibialis anterior muscle. It is located on the lower leg (the shin) and aids in moving the foot up, or the toes closer to the shin.

ISBN: 978-960-474-333-9

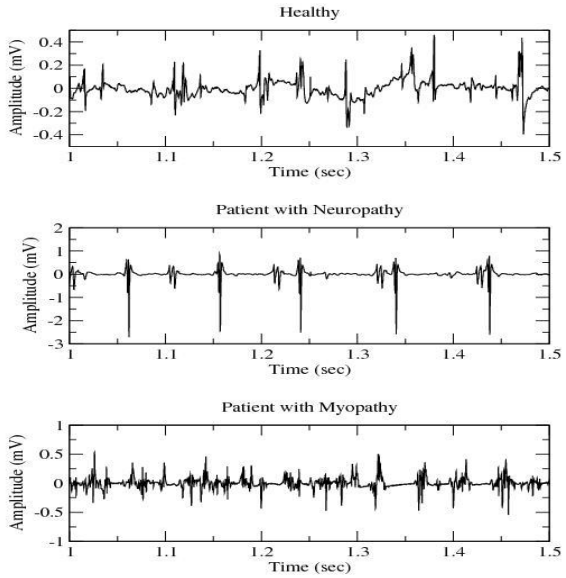

Fig. 1 Normal, neuropathic, and myopathic EMG signals [1]

2 EMG Structure

A typical electromyograph (EMG) consists of three main parts: three electrodes, a multi-stage high gain amplifier, and some form of digital signal processing. Figure 2 is a block diagram of what the structure of an electromyograph typically looks like.

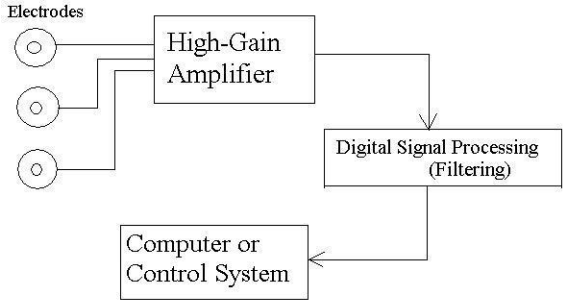

Fig. 2 General electromyograph structure

There are two different types of EMG's, classified based on the type of electrode used. Intramuscular electromyography (IEMG) is done by inserting needle electrodes or a needle containing two fine-wire electrodes through the skin into the muscle tissue. A trained professional is authorized to read the electrical signal activity after inserting the electrode. As a downside, intramuscular EMG may be considered too invasive and uncomfortable, especially for younger patients.

Instead, a surface, or stick-on, electrode may be used to monitor the general function of the muscle's activation, instead of the activity of a select number of fibers [2]. Surface electromyography (SEMG) reads the muscle signals from the surface of the skin and can be a better choice since it is less invasive and does not cause electrical irritation in the muscles. This irritation, which is caused by insertion of the needle electrodes, can muddle the information obtained by the EMG. The surface electrodes are stuck to the skin at three points: at the middle of the muscle, at the end of the muscle, and at a bony portion of the limb, such as on the elbow or knee.

Myoelectric signals are quite small, in the range of tens-of-microvolts to tens-of-millivolts, depending on the muscle being measured. As such, the amplifier portion of the EMG is essential. One researched example of an electromyograph had a total gain of 1200V/V. Of special importance is the instrumentation amplifier, as its high common-mode rejection ratio cancels out much of the noise picked up by the natural antenna that is the human body.

Other noise, including the 60 Hz frequency that is common to most AC-powered electrical equipment, must be filtered out using the digital signal processing stage of the EMG. The 60 Hz band is removed using a band stop or notch filter. This type of filter must be used, as 60 Hz is in the middle of the 0-to-500 Hz common range of frequency of the myoelectric signals [3]. The exact values differ based on whether the patient is healthy, or is suffering from myopathy or neuropathy.

Other sources of noise or distortion include skin resistance or motion artifacts, clipping, baseline drift, and processing errors [4].

3 Signal Analysis and Modeling

As shown in Figure 1, three EMG signals were obtained from the PhysioNET database: one from a healthy patient, one from a patient with neuropathy and one from a patient with myopathy. The signals are analyzed to determine defining characteristics as well as relative differences between the three types. The modelling is done to create ideal signals to compare to the received voltages. Results of the comparison will provide information to the control system which correction maneuver, if any, should be done. For modelling, autoregressive, fuzzy logic, or neural network systems can be used to model various signals. In this case, autoregressive modelling was implemented.

To better assess the difference in signals, spectrogram analysis was performed on each of the signals using MATLAB. Creating a spectrogram using the Short-Time Fourier Transform (STFT) is a

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process in which data sampled in the time domain, is broken up into segments and Fourier-transformed to calculate the magnitude of the frequency spectrum for each portion. Each piece then corresponds to a vertical line or block in the image. The pieces are then laid side by side to form the image.

The continuous wavelet transform was also used on each signal. A wavelet transform (WT) is used to divide a continuous-time function into wavelets. In contrast to the STFT, the continuous wavelet transform possesses the ability to construct a time-frequency representation of a signal that allows frequency and amplitude to be located at a particular time. Analysis of the provided signals will aid in the modelling of clinically obtained muscular signals.

The wavelet transform can be performed by using different wavelet families. Each of these families has a particularly shaped mother wavelet which is then compressed and/or dilated. These differing shapes allow the analyzer to get more information from the signal that is being studied. The wavelet family whose shape more similarly matches the original signal waveform will give more information about that signal. For each of these myoelectric signals, both the Morlet and Daubechies wavelets were utilized. In all three cases, the Morlet wavelet was found to give more accurate information about the original signal.

For the healthy patient, when the muscle is smoothly contracted, action potentials begin to appear. As the strength and duration of the muscle contraction are increased, an increased number of muscle fibers produce action potentials. When the muscle is fully contracted, there should appear a non-periodic and apparently random group of action potentials of varying rates and amplitudes. When the muscle is not contracted, there should be no electrical activity whatsoever. Figure 3 is the MATLAB-plotted values of a healthy tibialis anterior muscle obtained from PhysioNET.

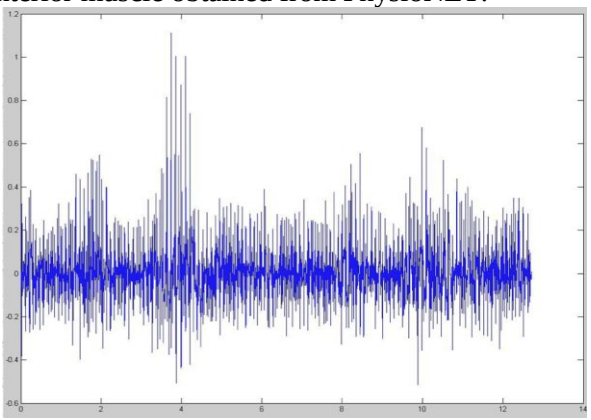

Fig. 3 Healthy EMG

Time (in seconds) is along the horizontal axis, and the voltage (in millivolts) is along the vertical axis. Figure 4 shows the spectrogram of the healthy patient's myoelectric signal.

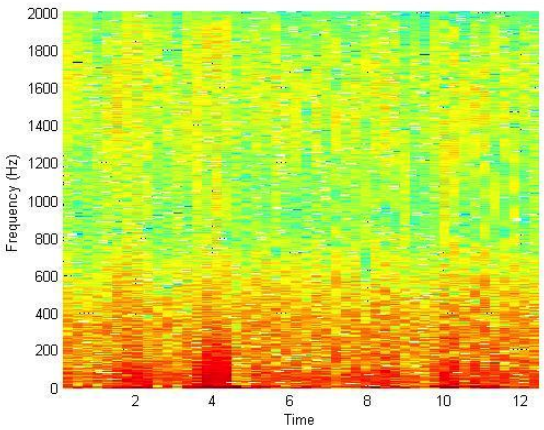

Fig. 4 Spectrogram of healthy EMG

The spectrogram shows varying frequencies from 0-to-600 Hz. Most are lower amplitudes but the darker color at two seconds, four seconds, and ten seconds shows higher-amplitude signal components. This correlates with the data from the original signal. Figure 5 shows the Continuous Wavelet Transform (CWT) of the healthy signal using the Daubechies 4 wavelet.

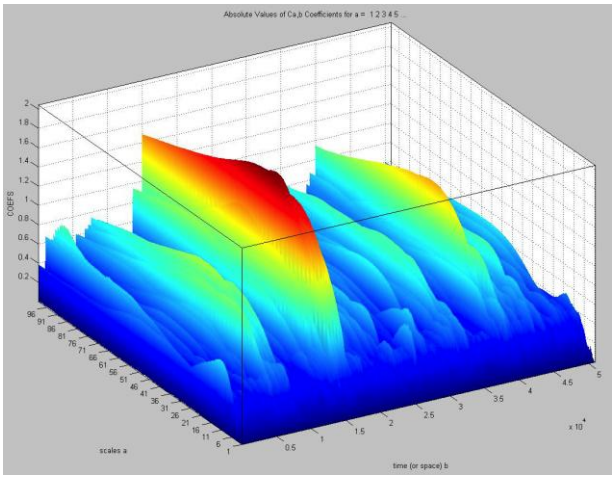

Fig. 5 Daubechies CWT of healthy signal

The CWT shows a three-dimensional view of the time-frequency representation of our healthy signal. It is a smooth graph due to the difference in shape of the Daubechies 4 wavelet as compared to the waveform of the EMG signal. Figure 6 shows another form of the CWT called the Morlet Wavelet.

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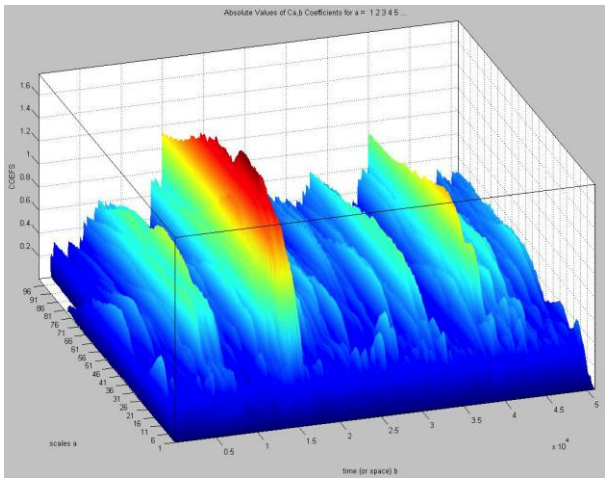

Fig. 6 Morlet CWT of healthy signal

Here the signal has a more jagged response due to the Morlet wavelet being very similar to the shape of the healthy individual's muscular waveform. The wavelets verify the spectrogram results that there are varying frequencies present the whole time, most of which have low amplitudes. The only exceptions are those amplitudes located as seen in Figures 2 and 3, at times of two-, four-, and ten-seconds.

A person suffering from myopathy has damage within the muscle itself. There is a decrease in the duration of the action potentials. The myopathy signal in Figure 7 shows that the amplitude voltages change more quickly and that the action potential duration shortens.

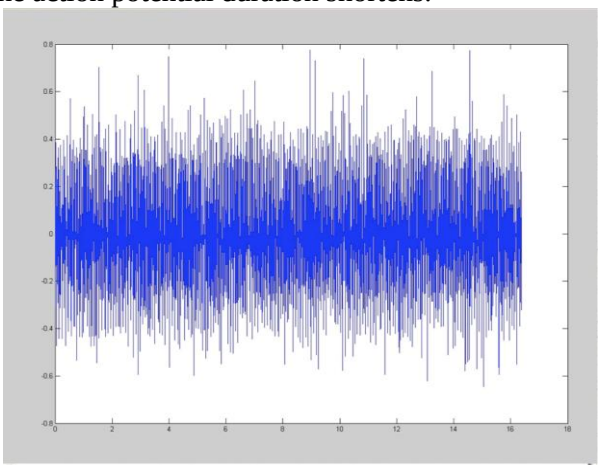

Fig. 7 Myopathic EMG

The spectrogram version of the myopathy signal in Figure 8 shows varying frequencies with medium to high amplitudes. Highest amplitudes are from 0-to-1000 Hz, which are present the whole time the data was being recorded.

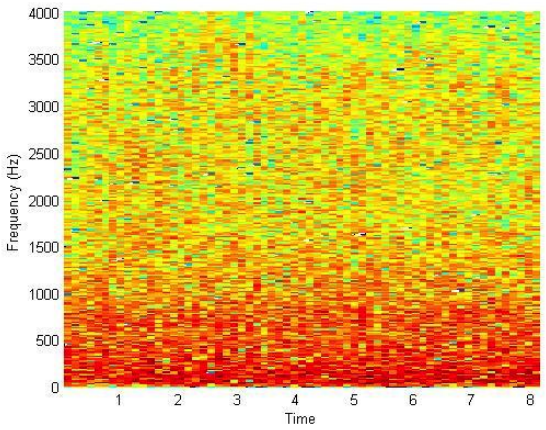

Fig. 8 Spectrogram of myopathic EMG

The Daubechies wavelet (Figure 9) shows a smoother representation of the myopathy signal, which still verifies the characteristics of a patient with myopathy.

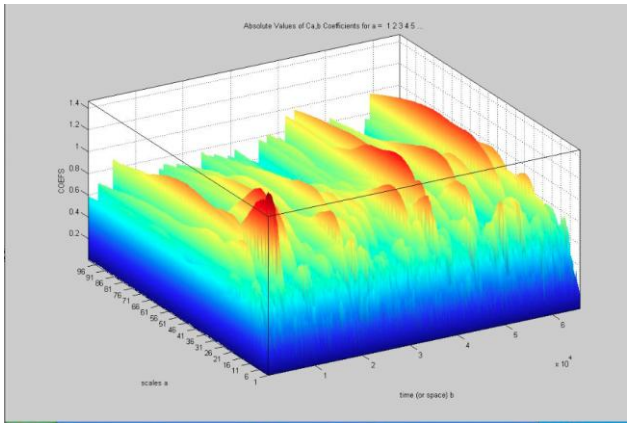

Fig. 9 Daubechies CWT of myopathic signal

The Morlet wavelet (Figure 10) however, shows that the amplitudes are actually higher than the Daubechies results suggest.

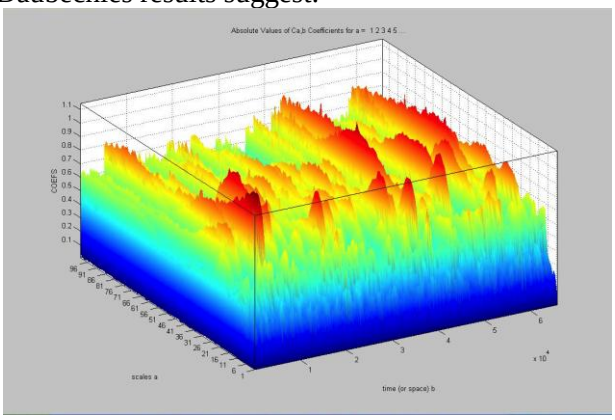

Fig. 10 Morlet CWT of myopathic signal

ISBN: 978-960-474-333-9

A person who suffers from neuropathy has endured damage to the nerves inside the muscles. An EMG of a person with neuropathy will show an increase in duration of the action potentials. It will also show a decrease in the reaction time of the remaining motor neurons because of the attempt to compensate for the damaged or missing ones. Figure 11 shows the plotted data from the patient with neuropathy.

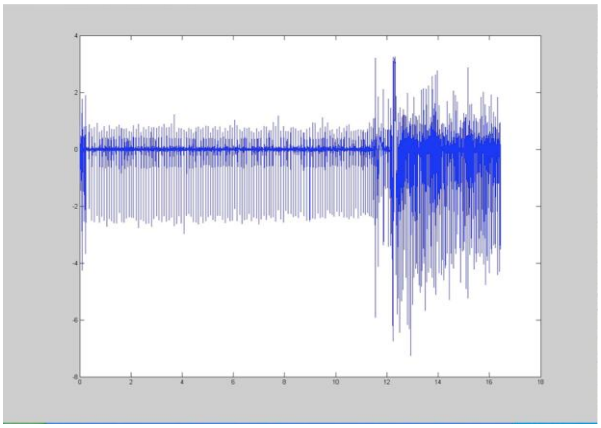

Fig. 11 Neuropathic EMG

It is unknown whether the higher-amplitude signal component starting at approximately eleven seconds is an error or part of the useful data. Figure 12 is the spectrogram of the neuropathic patient's electromyogram.

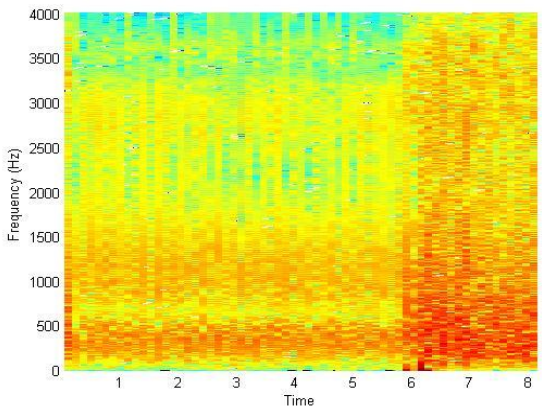

Fig. 12 Spectrogram of neuropathic EMG

It shows medium-high amplitude frequency bands at 400 Hz and 1100 Hz, and a medium amplitude frequency band at 3000 Hz. All amplitudes after twelve seconds are high and of varying frequencies, which correlates with the graphing of the raw data results. The wavelets shown were taken using scales from 25 to 225, which emphasizes the lower frequencies. Both are approximately the same shape, with low amplitudes up to the very high amplitude shown in the data and spectrogram. The Morlet CWT shows higher amplitude at that point than the Daubechies CWT shows (Figures 13 and 14 respectively).

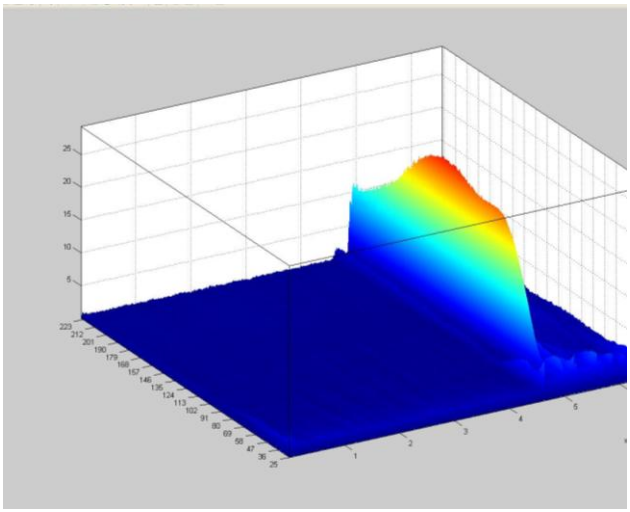

Fig. 13 Daubechies CWT of neuropathic signal

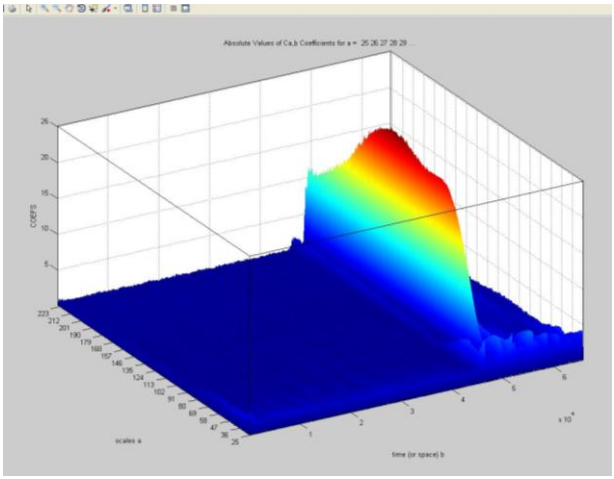

Fig. 14 Morlet CWT of neuropathic signal

It is necessary to create, or model, versions of these signals that could be implemented in a control system strategy. As stated earlier, autoregressive modelling was implemented to accomplish this. Successful completion of this processing shows that the modelled signals, illustrated by the thicker, smoother line, stay approximately true to the behavior and expectation of the original signals, which are shown with a thinner, more variable line. Figures 15-17 show each EMG and accompanying model, one with a healthy EMG signal, one with myopathy and one with neuropathy respectively.

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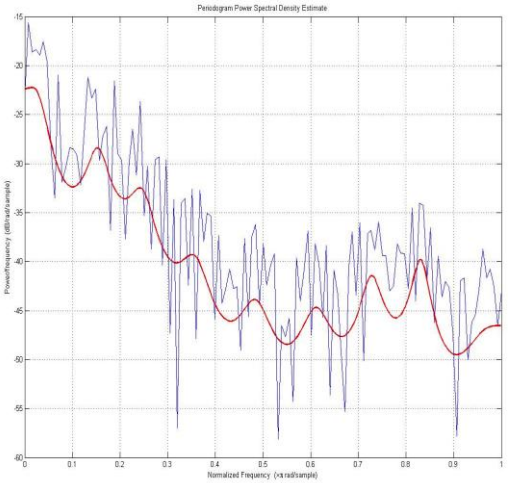

Fig. 15 Healthy signal and model

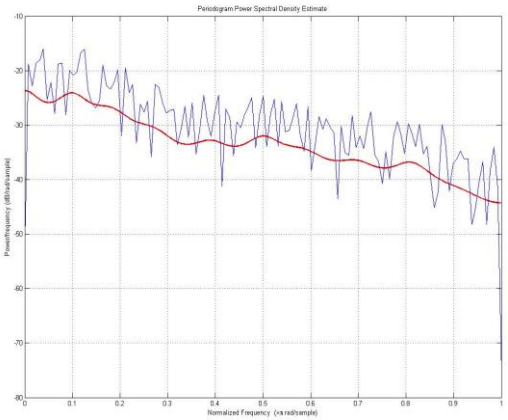

Fig. 16 Myopathic signal and model

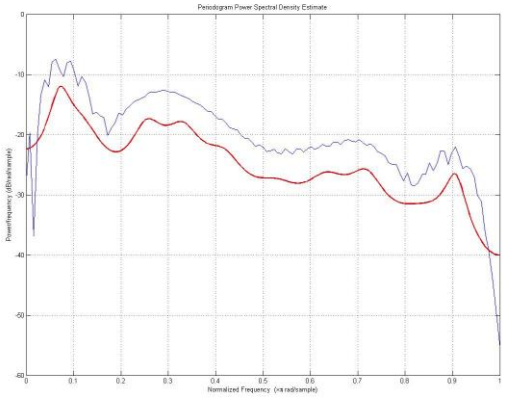

Fig. 17 Neuropathic signal and model

Each model uses the Yule-Walker autoregressive method to obtain its coefficients. This method estimates the power spectral density of the signal by creating an autoregressive model that fits the sectioned or windowed input data [5]. These particular models had a model order of twenty (i.e., 20 coefficients). Human speech, the most complicated commonly-modelled signal, requires a model order of fourteen coefficients to create a sufficient model. Twenty was decided on as a good model order, as one that should create an even higher-fidelity signal, without relying on an unnecessarily large number of coefficients. Due to the amount of variation in the signals as a whole, the modeling would need to be performed on blocks of data. Ideally, multiple models could be made of each signal to facilitate in the matching process used by the control system.

4 Control System

A control system utilizing the results of the signal modeling and analysis can be implemented in a number of different ways. The flow chart in the Appendix specifies that the spectrograms be compared, but a similar processing operation can be followed to compare the autoregressive models or the wavelet transforms.

The spectrograms – and, the autoregressive models in particular – work well for this application. They give general information about the signal, which allows for the natural differences between various patients. Without this generalization, it would be nearly impossible to be able to match any two signals, and even more difficult to ensure that the correct match (i.e., diagnosis of myopathy or neuropathy) would be made.

In a clinical setting, the electromyograph would record ten seconds of muscle activity data, which was the approximate length of the data sets from PhysioNET. The microcontroller would then take a spectrogram of the received signal using a Hanning window with an overlap of zero. It would then compare this spectrogram in succession to those stored of a healthy individual, an individual with myopathy, and an individual with neuropathy.

The matching process would have a slight variance to provide allowance for differences between patients. With a 75% match or better, the braces would be adjusted for one of three actions. If the spectrogram matched that of a healthy patient, no additive processing would occur for the braces. Generally, no corrective action would be needed for a healthy individual, but the data would still be available to the device for comparison purposes. If the spectrogram of the received signal matched that of a patient with myopathy, the braces would be setup to provide the maximum support. This action was chosen because myopathy causes more weakness in the muscles than neuropathy causes. If the spectrogram matches that of a patient with

ISBN: 978-960-474-333-9

neuropathy, then the braces would be setup to provide a slight amount of additional support and stability, as maximum support would be unnecessary.

In everyday use, a Bluetooth transmitter could be used to send a text or email to the doctor in the event of brace malfunctions.

4 Conclusion

Signal processing and analysis play an important part in utilizing electromyograms to control a rehabilitative or assistive device. In particular, parameter estimation can be used to create models that can be utilized by the assistive technology's control system to aid in increasing the patient's ability to perambulate on their own.

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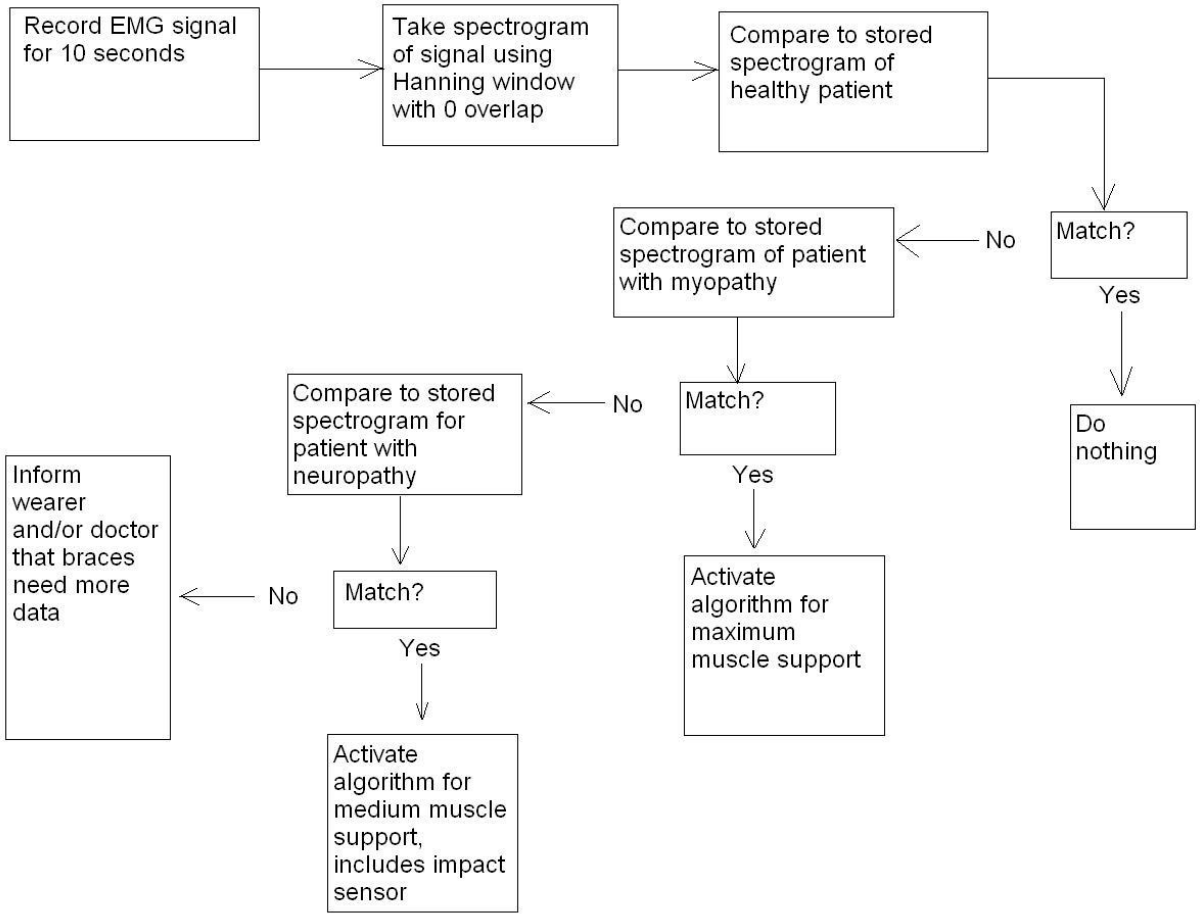
Appendix



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