Analysis of EMG Signal to Evaluate Muscle Strength and Classification

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Abstract – *Electromyography (EMG) is the study of muscle function through analysis of the electrical signals generated during muscular contractions. In this paper real time recording of EMG signals from Neuropathy, Myopathy, and healthy subjects, using intramuscular EMG (needle EMG) are treated and processed in order to classify for the diagnosis of neuromuscular pathology, feature extraction for EMG signals is done both in Time and Frequency domain to find energy of muscles in disorder and healthy muscles it is evaluated and classified using support vector machine.*

Key Words: *EMG, Neuropathy, Myopathy, Energy, SVM, Time and Frequency domain features.*

1. INTRODUCTION

Electromyography (EMG) is a diagnostic procedure that evaluates the health condition of muscles and the nerve cells that control them. These nerve cells are known as motor neurons. They transmit electrical signals that cause muscles to contract and relax. An EMG translates these signals into graphs or numbers, helping doctors to make a diagnosis. In this paper three muscle conditions like neuropathy, myopathy and healthy are evaluated and classified. Automated diagnostic of muscular diseases is becoming very important due to the increasing number of patients. Electrical signal generated at the muscle fibers can be used to analysis to detect abnormalities, activation level. EMG signal is complicated, non-stationary and random in nature [1].

Myopathy is a group of disorders characterized by a primary structural or functional impairment of skeletal muscle. Usually the muscles are affected without involving the nervous system, resulting in muscular weakness. Neuropathy is a disorder that affects your body's motor nerves. Those are the nerves that control our muscles. The condition makes it hard for them to send the electrical signals that move your body, which makes your hands and arms feel weak. Neuropathy signals usually have very high amplitudes than healthy and myopathy signals.

In this paper classification of the EMG signals and to evaluate strength of the muscle in muscle disorder patients is done, to achieve this following steps includes Pre-processing, Time and Frequency domain feature extraction. Raw EMG signals are first high passed, Full wave rectified, Low Passed and Notch filtered and the output is fed to Time and Frequency domain feature extraction. To evaluate muscle strength of different disorders the time dependent average values of RMS value, mean and median frequencies of myopathy neuropathy and healthy signals are compared, by comparing the time dependent values one can know the energy of different disorder muscles.

2 MATERIALS AND METHODS

EMG signals are collected from 16 patients (5 Normal, 7 Neuropathy and 4 Myopathy). The NIHON KOHDEN MEB_2300K machine with 25 mm concentric needle is used to collect raw EMG signals. Electrodes are connected to an electronic device referred to as differential amplifier. This device has two inputs and one output. The output is a potential that is the difference between the two input (electrode) potentials.

The collected data commonly contain noises. Corrupted EMG signals are the major problem in the analysis. A signal enhancement (pre-processing) consists two steps: Filtering and Rectification is applied to extract unintended features. Features in the time domain have been extracted here for the evaluation of energy. These features are widely used in medical and engineering practices and researches.

Raw EMG data is high-pass filtered at 10-15 Hz or higher, to remove movement artefacts depending on the activity. The signal absolute value is taken this is also known as full wave rectification. Clinical EMG data is usually low-pass filtered at 1,000 Hz or higher for needle EMG recordings and sampling frequency of 2000Hz is preferable [1].

The forward reverse digital filtering with filtfilt has the advantage of no time shift compared to unidirectional filters. Ambient noise originates from sources of electromagnetic radiation, such as radio and television transmission, electrical-power wires, fluorescent lamps etc. The surfaces of our bodies are constantly exposed to electromagnetic radiation and it is impossible to avoid this exposure. The dominant concern for the ambient noise arises from the 50 Hz (or 60 Hz) radiation from power sources. Then the feature extraction is done both in time and frequency domain.

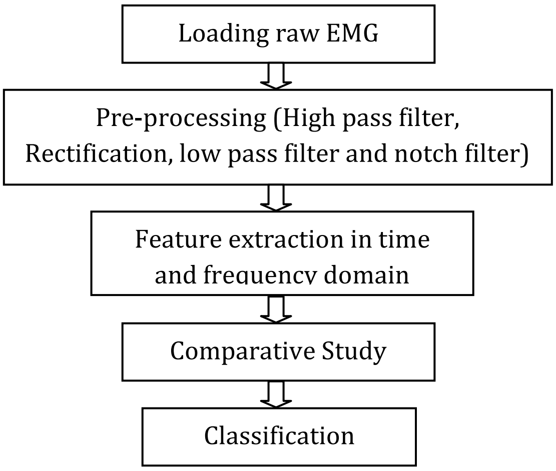

Fig-1: Block diagram of the proposed Analysis of EMG signal to evaluate muscle strength using Time domain and classification using Time and Frequency Domain Method

In order to analyze the EMG power spectrum in both of muscle force and fatigue indices, we investigate a time dependence of the MDF and the MNF of a time-sequential data. Commonly used EMG features RMS, MDF and MNF were calculated in this study [2], [3].

2.1 Time Domain Features

Features in the time domain have been widely used in medical and engineering practices and researches. Time domain features are used in signal classification due to their performance in signal classification in low noise environments, their lower computational complexity, and easy and quick implementation. Furthermore, the features are calculated based on raw EMG time series. The time domain features assume the data as a stationary signal. Moreover, much interference that is acquired through the recording because of their calculations is based on the EMG signal amplitude [1], [2], [3], [4].

2.1.1 Root Mean Square (RMS):

It is the square root of the mean of squares of individual values.

RMS can be calculated by

$$RMS = \sqrt{\sum_i^N x_i^2} \qquad (1)$$

where x_i is the EMG signal and N is the length of the EMG signal.

2.1.2 Median Frequency (MDF):

MDF is a frequency value at which the EMG power spectrum is divided into two regions with an equal integrated power [4].

it is calculated by

$$\sum_{j=1}^{MDF} P_j = \sum_{j=MDF}^{M} P_j = \frac{1}{2}\sum_{j=1}^{M} Pj \qquad (2)$$

where *Pj* is the EMG power spectrum at a frequency bin *j* and *M* is the length of frequency bin. Power spectra density *P* was calculated by the method of Periodogram Welch.

2.1.3 Mean Frequency (MNF):

MNF is an average frequency value that is computed as a sum of product of the EMG power spectrum and frequency, divided by a total sum of spectrum intensity. It is commonly used to examine fatigue in muscular disorder patients [3], [4], [5].

It can be expressed as

$$MNF = \frac{\sum_{j=1}^{M} f_i P_j}{\sum_{j=1}^{M} P_j} \qquad (3)$$

where *Pj* is the EMG power spectrum at a frequency bin *j* and *M* is the length of frequency bin and f_i is a frequency value at a frequency bin *j*.

2.1.4 Mean Absolute Value(MAV):

It represents the area under the EMG signal once it has been rectified, meaning that all of the negative voltage values have been made positive. The MAV is used as a measure of the amplitude of the EMG signal

$$Mean\ absolute\ value = \frac{1}{N}\sum_i^N x_i \qquad (4)$$

where x_i is the EMG signal and N is the length of the EMG signal.

2.1.5 Integrated EMG:

The total amount of muscle activity during a given duration of the signal gives integration value. It can also be calculated by finding the area under the curve during the active duration. More amplitude, duration and frequency of action potentials lead to the large value of integration. Raw EMG signal is a bi-polar signal,

$$Integrated\ EMG = \sum_{i=1}^{N} x_i \qquad (5)$$

where x_i is the EMG signal and N is is the length of the EMG signal.

2.1.6 Number of Peaks:

Number of peaks is usually higher in neuropathy signals then healthy and myopathy signals.

2.1.7 Variance:

It is the average of squared values of the deviation of the EMG signal and variance is calculated using the given formula,

$$Variance = \frac{1}{N-1}\sum_i^N x_i^2 \quad (6)$$

where x_i is the EMG signal and N is the length of the EMG signal.

2.2 Frequency Domain Features:

Frequency domain analysis means finding the various sinusoidal components inside the EMG signal. The energy distribution of the signal with frequency can be found. The amplitude of the corresponding frequency component is detected. Muscle conditions, the shape of the motor unit and conduction velocity affect the spectrum. Firing rate and amplitude do not affect the spectrum shape. Fast Fourier transform function (FFT) is the well known and easy to use technique to analyze signals in the frequency domain.

The Fourier Transform: A Fast Fourier Transform (FFT) is an efficient algorithm to compute the Discrete Fourier Transform (DFT) and its inverse. This means that it becomes (relatively) simple to jump between the time domain and the frequency domain of a data series or signal. If the signal is a sample of the actual event, the Discrete Fourier Transform is used. The discrete Fourier transform yields a close approximation to the continuous Fourier transform.

Frequency Analysis decomposes this signal into sinusoidal components of different frequencies enabling the direct measurement of the energy distribution of the signal, as a function of the frequency components of the signal. Essentially, this provides the electromyographer with a direct measurement of the amplitude of frequency components of the EMG signal, grouped the frequencies at which the muscles fire.

The frequency domain features are as follows:

2.2.1 Average Power Spectral Density (PSD):

The power spectrum of a signal describes the distribution of the signal's power with frequency and is calculated by squaring the Fourier Transform of each segment of data and averaging them. This gives a measure of the power that each frequency contributes to the EMG signal.

$$S_x(f) = |X(f)|^2 \quad (7)$$

where $X(f)$ is the Fourier Transform of the EMG signal.

2.2.2 Mean Frequency:

The mean frequency is that frequency where the product of the frequency value and the amplitude of the spectrum are equal to the average of all such products throughout the complete spectrum.

It can be expressed as

$$MNF = \frac{\sum_{j=1}^{M} f_i P_j}{\sum_{j=1}^{M} P_j} \quad (8)$$

where *Pj* is the EMG power spectrum at a frequency bin *j* and *M* is the length of frequency bin and *fj* is a frequency value at a frequency bin *j*.

2.2.3 Median Frequency: It is the frequency at which 50% of the total power is reached. It decomposes the surface under $S_x(f)$ into two equal areas.

$$\int_0^{F_{med}} S_x(f)\,df = \int_{F_{med}}^{F_{max}} S_x(f)\,df \quad (9)$$

2.2.4 Spectral entropy: Entropy describes the irregularity or unpredictability characteristics of the signal.

$$H = -\int_0^{f_{max}} S_x(f) ln[S_x(f)]\,df \quad (10)$$

3 RESULTS

In order to evaluate muscle strength the analysis of EMG power spectrum in both of muscle force and fatigue indices, we investigate a time dependence of the MDF and the MNF of a time-sequential data. Commonly used EMG features RMS, MDF and MNF were calculated in this study.

Table-1: Time domain feature values such as RMS value, Median frequency, Mean frequency of Right Biceps neuropathy disorder muscle

Force	RMS value	MDF	MNF
0kg	0.0073	0.5101	0.656
1kg	0.0162	0.577	0.7103
2kg	0.0187	0.8209	0.9478

Table-2: showing Time domain feature values of Right Biceps Myopathy disorder muscle

Force	RMS value	MDF	MNF
0kg	0.0084	0.4088	0.5935
1kg	0.0077	0.5183	0.69
2kg	0.0072	0.6917	0.8013

Table-3: Time domain feature values of Right Biceps Healthy muscle

Force	RMS value	MDF	MNF
0kg	0.0073	0.581	0.722
1kg	0.0079	0.7035	0.8334
2kg	0.009	0.1582	0.3963

Figure 2 shows the RMS difference between Neuropathy, Myopathy and Healthy gradually and significantly became larger with increasing load forces and neuropathy and myopathy status, the RMS at neuropathy patients was significantly larger than healthy importantly. In a neuropathy muscle work with higher frequencies to achieve the same movement of muscle, as the neurons are not functioning properly, but muscle motor units are working goodly. For myopathy efforts are given for the movement, but motor units are affected due to this RMS amplitude and operating frequency is less. Healthy muscle, there is no need of extra effort for contraction; therefore it works at low frequencies compare to neuropathy.

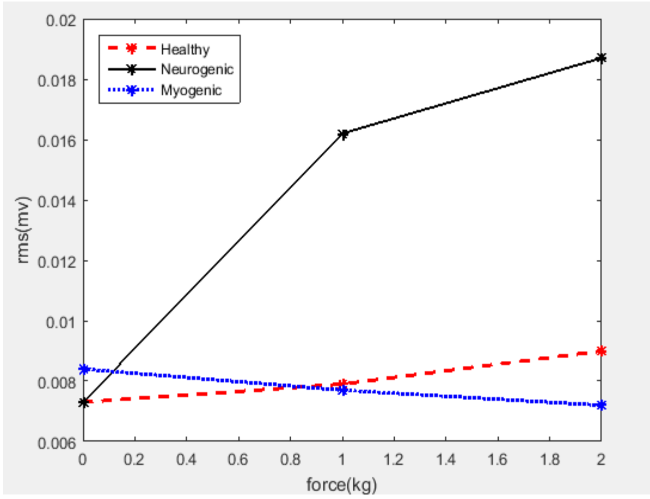

Fig-2: RMS values b/w healthy neuropathy and myopathy

For the effect of muscle force, the selection of time-dependent MNF and MDF should be applied to the raw EMG data. As a result, MNF and MDF should increase as the muscle force or load increases figure 3.2 shows MDF at neuropathy and myopathy condition were significantly increases than healthy EMG signal. The results showed that mean and median features of the EMG signals have a better linear relationship with muscle force (load level).

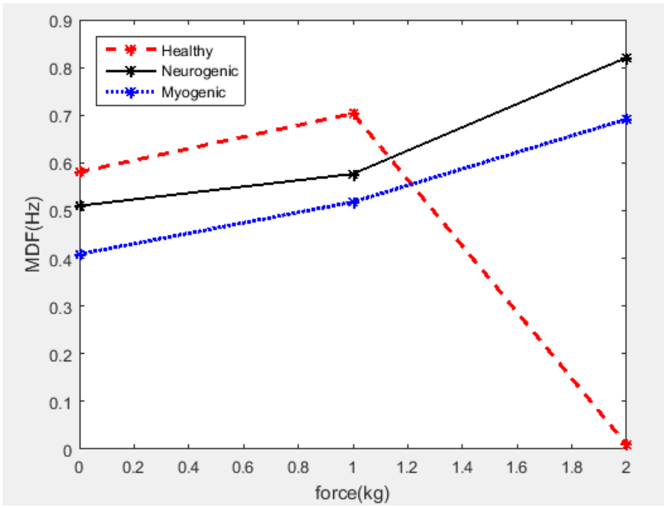

Fig-3: MDF values b/w Healthy Neuropathy and Myopathy

Whereas MNF at neuropathy and myopathy signals significantly increases than healthy signal as shown in figure 3

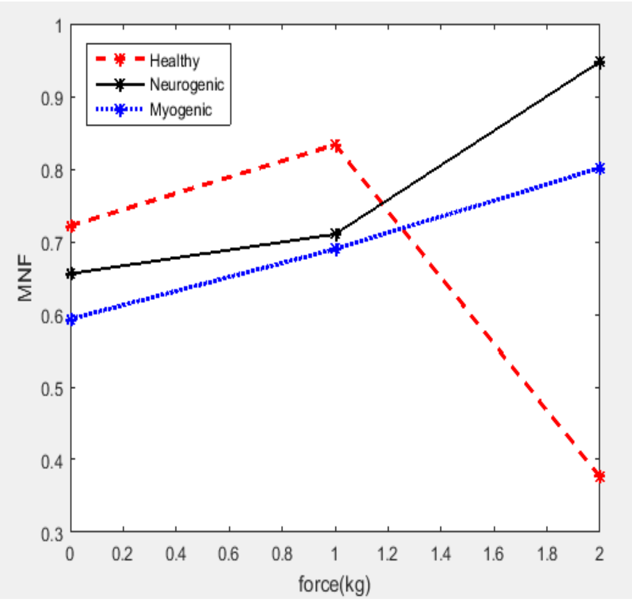

Fig-4: Mean frequencies for healthy neuropathy and myopathy

Table-4: showing average Time domain parameters values of Neuropathy Myopathy and Healthy signals

	Neuropathy	Myopathy	Healthy
RMS value	3051.4865	252.004	2279.709
Integrated EMG	1129.7717	132.0667	888.1077
MAV	0.0056	0.0007	0.0044
Variance	46.9855	0.3196	26.2064
Number of peaks	505	2	141

By comparing the average values number of peaks, RMS value, integrated value and Variance we can differentiate between neuropathy myopathy and healthy signals. Number of peaks will be higher is Neuropathy signals then healthy and myopathy EMG. So it can be used to differentiate between neuropathy and healthy signals.

In frequency domain average values average power, entropy and energy of the EMG signals can be used to differentiate between the signals

Table-5 showing average Frequency domain parameters values of Neuropathy Myopathy and Healthy signals

	Neuropathy	Myopathy	Healthy
Average power	11.6016	0.0557	1.8373
Median frequency	0.4301	0.4065	0.2338
Mean frequency	0.5547	0.5141	0.4115
Entropy	963.146	14.2652	371.9881
Energy	46.9853	0.3196	26.2062

4. CONCLUSION

To evaluate muscle strength of different disorders the average values of RMS value, mean and median frequencies of myopathy neuropathy and healthy signals are compared, By comparing RMS values of EMG signals for neuropathy, healthy and myopathy muscles, we can conclude that, if a muscle is not healthy it has to work more for large conduction velocities, at the higher amplitude and at higher frequency. In a neuropathy muscle, it work with higher frequencies to achieve the same movement of muscle, as the neurons are not functioning properly, but muscle motor units are working good. Healthy muscle, there is no need of extra effort for contraction; therefore it works at low frequencies compare to neuropathy. For myopathy efforts are given for the movement, but motor units are affected due to this RMS amplitude and operating frequency is less.

MNF and MDF are frequently used as the standard tool to detect fatigue in the target muscles using EMG signals. Due to the fact that muscle fatigue results in an increase of EMG signal amplitude, time-domain features based on energy information, i.e. IEMG, MAV and RMS, can track this behavior. For the effect of muscle force, the selection of time-dependent MNF and MDF should be applied to the EMG data. As a result, MNF and MDF should increase as the muscle force or load increases. Here in the neuropathy and myopathy EMG signals MNF and MDF gradually increases as force increased, so the neuropathy and

myopathy patients needs to be treated to gain muscle strength by regular comparison on EMG signal values.
By comparing the feature values of healthy neuropathy and myopathy EMG signals it can be concluded that with statistical parameters and the features of signal, it is easy differentiate between healthy, myopathy and neuropathy disorder. By this we could know Strength of healthier muscles will be more than neuropathy and myopathy patients. Further study can be done by considering the gender, age of the patients for better performance.

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