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COMPARISON OF NORMAL AND PATHOLOGICAL GAIT USING EMG SIGNAL

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ABSTRACT

Due to poor lifestyle and posture people all over the world are suffering from lower limb muscle diseases.The diagnosis and designing of prosthetic leg can't be done by observation only. The performance of the muscles are affected by three factors i.e. strength, power and endurance. There are three factors that affect how well your muscles perform – strength, power and endurance. Many studies have proposed co-relation of muscle activity in terms of s-EMG which is observed inside body muscle.In this work, a case-study has beenconducted over five pathologically affected males of 23±3 years of age and 60±10 kg weight whose one leg was affected. Power spectral density (PSD) and Mean frequency (MNF) of 'Lateral Gastrocnemius' muscle during normal GAIT cycle was determined. The PSD data so obtained was analyzed using MATLAB. The determined data was analyzed through statistical analysis technique (MNF). It was observed that endurance strength of normal leg was less compared to pathological leg.

Keywords: EMG, GAIT, Lateral Gastrocnemius, Mean frequency, Prosthetic leg

I INTRODUCTION

Gait may be described as a translatory progression of the body as a whole, produced by coordinated, rotatory movements of the body segments. The body moves only because energy is generated by means of concentric contraction of muscle groups. Various phase of GAIT cycle is shown in Figure 1.

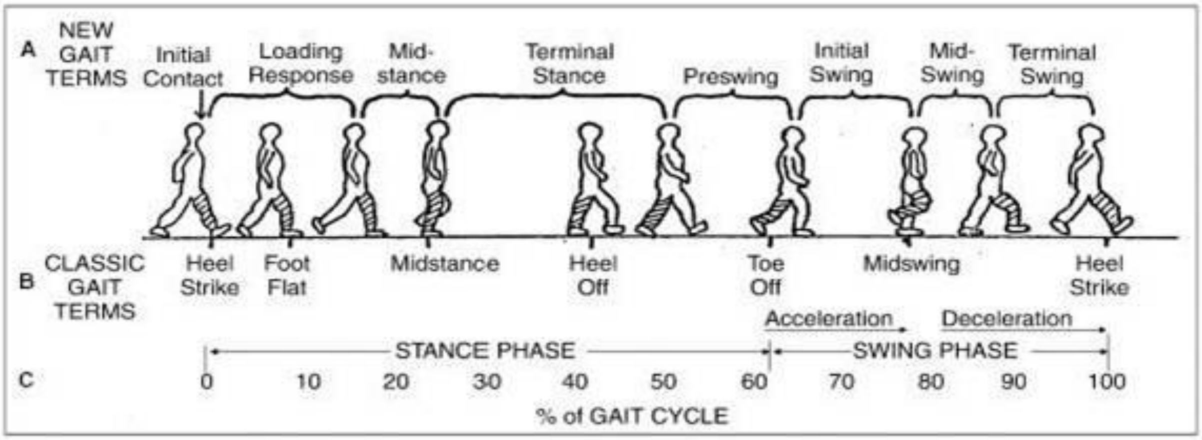

Fig. 1 Phases of gait cycle**[7]**

II METHODOLOGY

In order to perform analysis between pathological and normal leg, wavelet denoising is done and to remove the some wavelet coefficients sequence thresholding is also done. Average power of muscles is estimated using RMS technique. These methods were mentioned as followed.

2.1 Wavelet Denoising

Denoising is done to vanish those parts of the signal which are generated during normal normal condition. Discrete wavelet transform can be used for easy and fast de-noising of a noisy signal. The limited number of highest coefficients of the discrete wavelet transform spectrum, and an inverse transform (with the same wavelet basis) was performed to obtain more or less de-noised signal. There are several ways to choose the coefficients that may be espoused. In this paper,two methods namely hard and soft thresholding were performed. However, for experimentation, hard thresholding has been used.

Discrete wavelet thresholding has been done by three step processing, those steps are explained below:

1. Discrete Wavelet Decomposition
2. Thresholding
3. Reconstruction of the signal

2.1.1 Discrete Wavelet Decomposition (DWT).

It is computed by successive lowpass and highpass filtering of the discrete time-domain signal known as Mallet algorithm or Mallet-tree decomposition (MTD). Mallet algorithm signifies the manner it connects the continuous-time mutiresolution to discrete-time filters as shown in Fig. 2. The signal is denoted by the sequence x[n], where n is an integer. The low pass filter is denoted by G_0 while the high pass filter is denoted by H_0. At each level, the high pass filter produces detail information; d[n], while the low pass filter associated with scaling function produces coarse approximations, a[n].

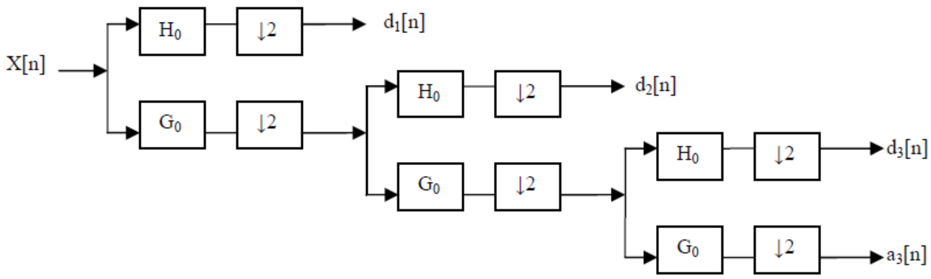

Fig.2Wavelet decomposition tree[7]

At each decomposition level, the half band filters produce signals spanning only half the frequency band. This doubles the frequency resolution as the uncertainty in frequency is reduced by half. In accordance with Nyquist's rule if the original signal has a highest frequency of ω, which requires a sampling frequency of 2ω radians, then it will have a high frequency of ω/2 radians. It can be sampled at a frequency of ω radians, thus, discarding half the samples with no loss of information.

2.1.2 Thresholding

Thresholding is the methods to remove the some wavelet coefficients from the wavelet coefficient sequence and vanishing of these wavelet coefficients are based on firm mathematical expressions. There are many types of thresholding methods such as hard thresholding function and soft thresholding function.

A. Hard thresholding function:

The hard thresholding function is not continuous in the wavelet field, A and -A is the discontinuous points. This will cause difficulty in differential calculation. The hard thresholding function only treats the coefficients which are smaller than the thresholding value and leave the coefficients as usual which are bigger than the thresholding value. This contradicts the fact that there is noise in the coefficients which are bigger than the thresholding value. The expression of hard thresholding function:

$$\hat{\omega}_{j,k} = \begin{cases} \omega_{j,k}, |\omega_{j,k}| \geq \lambda \\ 0, |\omega_{j,k}| < \lambda \end{cases} \quad \ldots (1)$$

Where omega is wavelet coefficients and lambda is the threshold value.

B. Soft thresholding function:

Soft thresholding function is continuous in the wavelet field, but becomes discontinuous after its differentiation. Further, the soft thresholding value is constant such that the coefficients are reduced by a fixed value. This contradicts the fact that the noise Component gets greater as the coefficients decrease. The expression of soft thresholding function is given by:

$$\hat{\omega}_{j,k} = \begin{cases} \operatorname{sgn}(\omega_{j,k})(|\omega_{j,k}| - \lambda), |\omega_{j,k}| \geq \lambda \\ 0, |\omega_{j,k}| < \lambda \end{cases} \quad \ldots (2)$$

2.1.3 Reconstruction of the Signal

Fig.3 shows the reconstruction of the original signal from the wavelet coefficients. Reconstruction is reverse of decomposition. To acquire this, approximation and detail coefficients are sampledat every level, and passed through the low pass and high pass synthesis filters followed by summation. This process is continued for the same number as the decomposition process to obtainthe original signal. The Mallat algorithm works equally well if the analysis filters, G_0 and H_0, are exchanged with the synthesis filters, $G_{1\,1}$.

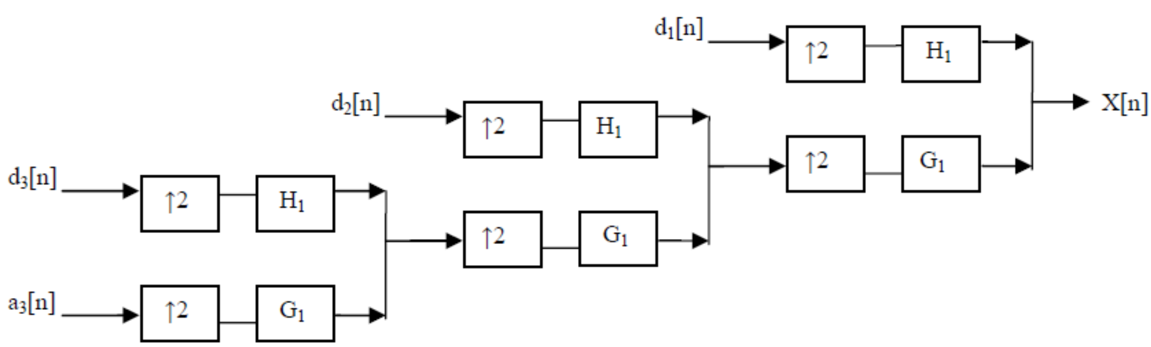

Fig. 3 Wavelet reconstruction tree [7]

2.2 Calculation of RMS value of de-noised EMG signal

The RMS value of signal represents power of the EMG signal.

The RMS value for discrete signal is calculated using Eqn 3

$$x_{\mathrm{rms}} = \sqrt{\frac{1}{n}\left(x_1^2 + x_2^2 + \cdots + x_n^2\right)}. \quad \ldots (3)$$

Where, $x_1, x_2, x_3 \ldots x_n$ are the n samples of the signal.

EMG is nonstationary signal and is its statistical features, distributed over the time dimension. RMS value for the whole signal gives the mixture of statistical features of EMG. However,these mixtures do not give significant result. Due to this,The RMS value was calculated over certain number of samples. The selection of the number optimize according to the sampling frequency of signal, length and requirement.

In this experiment RMS valuewere calculated for each 100 samples.

2.2.1 Estimation of average power of muscles during GAIT cycle

Square ofthe RMS value of an EMG signal represents the power of the signal. After observing the RMS-plot each muscle can be figure out in RMS-plot.

2.3 EMG Signal Processing

EMG signal processing is divided into the following parts

1. Wavelet de-noising.
2. Calculation of RMS value.
3. Calculation of Power spectral Density.
4. Calculation of Mean frequency.
5. Calculation of Median frequency.
6. Estimation of average power of muscles during each gait cycle.

2.3.1 Useful Variables of the EMG Signal

Two parameters are commonly used to measure the amplitude, the root-mean-square (RMS) value and the mean absolute (MA) value.

The power density spectrum of the EMG signal ranges from 0 to 400 Hz for most muscles. Above this frequency, the frequency components of the EMG signal have amplitude less than 1 micro-volts RMS and are no longer distinguishable from the noise of the detection and recording system. There are some exceptions, such as the masseter muscle, where the frequency distribution reaches up to 600 Hz. Consequently, it is recommended that the general representation of the frequency spectrum be considered to range up to 500 Hz.

a. Root Mean Square Value

The RMS represents the square root of the average power of the EMG signal for a given period of time.It is known as a time domain variable because the amplitude of the signal is measured as a function of time.

b. Mean Absolute Value

The MA value is the computer calculated equivalent of the average rectified value (ARV). The MA value is also known as a time domain variable because it is measured as a function of time. It represents the area under the EMG signal. Once EMG is rectified, thanonly positive values are obtained. The MA value is used as a measure of the amplitude of the EMG signal similar to the root mean square (RMS). The RMS is often preferred over the MA value because it provides a measure of the power of the EMG signal.

c. Median Frequency

The median frequency is defined as that frequency that divides the power density spectrum in two regions having the same amount of power.

d. Mean Frequency

It is the frequency at which the product of the frequency value and the amplitude of the spectrum is equal to the average of products throughout the complete spectrum.

e. Total Power (TTP)

TTP is an aggregate of EMG power spectrum. This feature defined the energy and the zero spectral moment. The equation for TTP is expressed as [7]

$$\mathrm{TTP} = \sum_{j=1}^{M} Pj \quad \ldots (4)$$

f. Mean power (MNP)

MNP is an average power of EMG power spectrum. It can be expressed as [7]

$$\mathrm{MNP} = \sum_{j=1}^{M} Pj/M \quad \ldots (5)$$

g. Peak frequency (PKF)

PKF is a frequency at which the maximum EMG power occurs. It can be expressed as [1]

$$PKF = \max(Pj),\ j=1,M. \quad \ldots (6)$$

h. Spectral Moments(SM)

SM is an alternative statistical analysis way to extract features from the power spectrumof EMG signal. Normally, the first three moments (SM1-SM3) are employed as the EMG Features. Their equations can be expressed by relation proposed by *Tagwa et al* [6]

$$\mathrm{SM1} = \sum_{j=1}^{M} Pj.fj\ , \mathrm{SM2} = \sum_{j=1}^{M} Pj.fj^2\ , \mathrm{SM3} = \sum_{j=1}^{M} Pj.fj^{\,3} \quad \ldots (7)$$

i. Frequency Ratio (FR)

FR is used to discriminate between relaxation and contraction of the muscle using a ratio between low- and high-frequency components of EMG signal. The equation is defined by *Jing et al*[3]

$$\mathrm{FR} = \sum_{j=LLC}^{ULC} Pj \,/ \sum_{j=LHC}^{UHC} Pj \quad \ldots (8)$$

where,ULC and LLC are respectively the upper- and the lower-cutoff frequency of low frequency band, and UHC and LHC are respectively the upper- and the lower-cutoff frequency of high-frequency band. The cutoff frequency between low- and high-frequencies can be defined by two ways: the experiment and the MNF value [2, 4]

j. Power Spectrum Ratio (PSR)

PSR is a ratio between the energy *P0* which is nearby the maximum value of EMG power spectrum and the energy *P* which is the whole energy of EMG power spectrum. It is an extended version of PKF and FR. The equation can be expressed as proposed by *Hogrel* [5]

$$\text{PSR} = \frac{P0}{P} = \sum_{j=f0-n}^{f0+n} Pj \,/\, \sum_{j=-\infty}^{\infty} Pj \qquad \ldots (9)$$

Where, *f0* is value of PKF and *n* is the integral limit.

k. Variance of Central Frequency

VCF is defined by using a number of the spectral moments (SM0-SM2) and MNF. It can be computed by the following equation

$$\text{VCF} = \frac{1}{SM0}\sum_{j=1}^{M} Pj(\text{fj-MNF})^2 = \left(\frac{SM2}{SM0} - \frac{SM1}{SM0}\right)^2 \qquad \ldots (10)$$

2.4 Usefulness of Mean Frequency

Mean frequency (MNF) is the most useful and popular frequency-domain features and frequently used for the assessment of muscle fatigue in surface EMG signals. Muscle fatigue is generally defined as an activity induced loss of the ability to produce force with the muscle. Usually, the muscle fatigue is a result of prolonged or repetitive work. Undetected fatigue for a long-time can cause injury to the subject and is often irreversible. Among such techniques, MNF has been hailed as the standard for muscle fatigue assessment with surface EMG signals due to the fact that muscle fatigue results in a downward shift of frequency spectrum of the EMG signal. Moreover, during the fatigue of the muscle, several changes have been found such as a relative decrease in signal power at high-frequency, a small increase in signal power at low-frequency, an increase in spectrum slope at high-frequency and a decrease in spectrum slope at low-frequency.

For understanding the effect of muscle force, the selection of time-dependent MNF should be applied to the raw EMG data. As a result, MNF should increase as the muscle force or load increases. Further for understanding the effect of muscle geometry or joint angle, the normalization technique should be applied to the raw EMG data. As a result, MNF should increase similar to the muscle length or joint angle (degrees of extension) decreases. [7]

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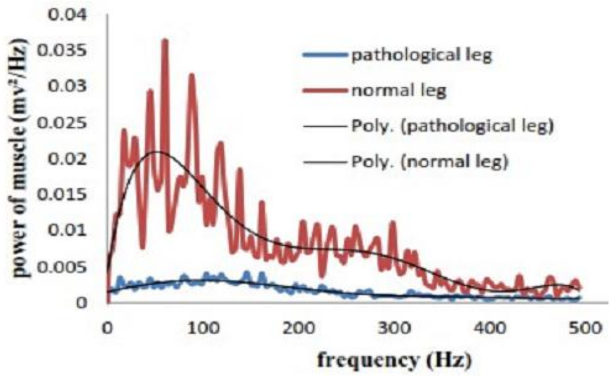
III RESULTS AND DISCUSSION

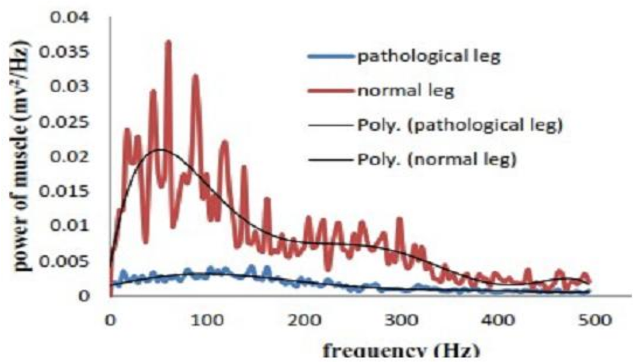
3.1 Lateral gastrocnemius

Subject 1



(a)

Subject 2



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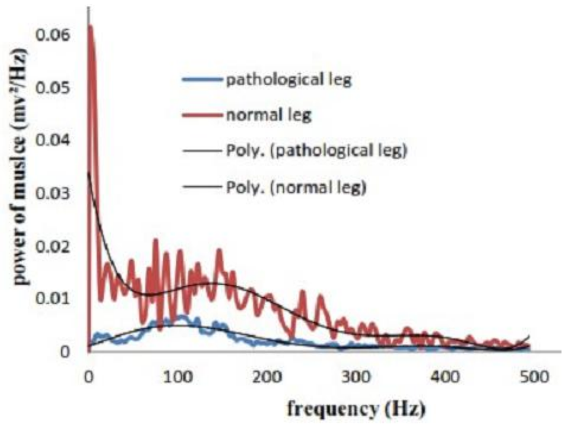

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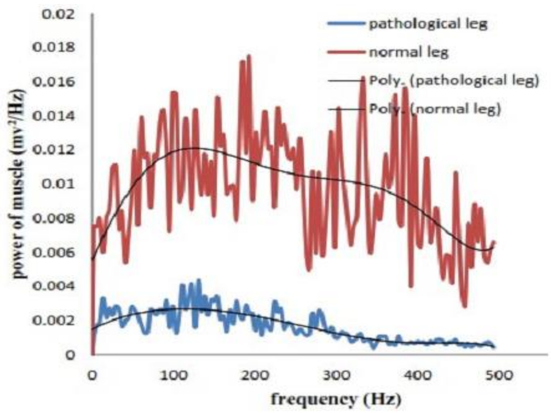

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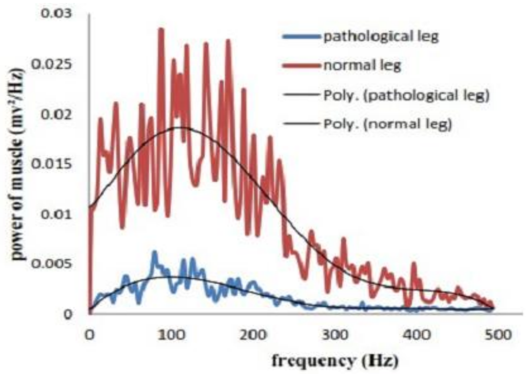


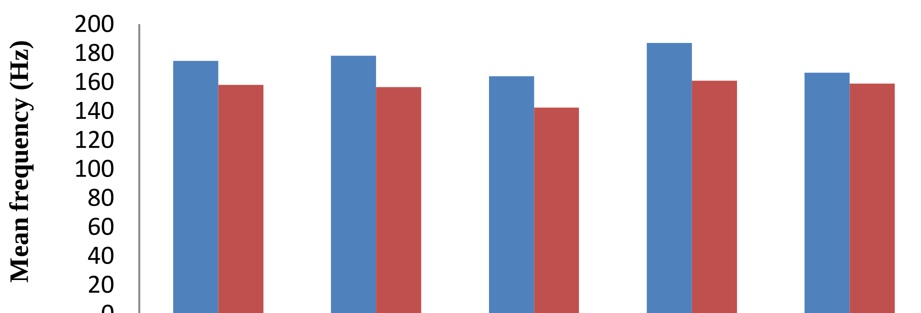
(e)

Fig. 4 Variation in Power of normal and pathological leg of Lateral gastrocnemius: (computed for 5 subjects)

Fig. 4 (a-e)shows the five cases of normal and pathological leg. The red line indicates the power of the muscle for normal leg with higher peak variations and the blue line indicates power of muscle for pathological leg with lower peaks. For normal leg, the value of the power of the muscle lies between 0.01 to 0.06 mv^2/Hz whereas in case of pathological leg it lies between 0 to 0.006 mv^2/Hz. It is clear from Fig 4 (a-e) that the normal leg has more power in the muscle as compared to pathological leg in all subjects. This is due to fact the normal leg contains natural strength which is obtained since birth and proper nutrition. But, in case of pathological leg due to lack of nutrition the leg becomes weak.

3.2 Variation of Mean Frequency of Normal and Pathological Leg of Lateral Gastrocnemius:

MNF vs No. of subjects



	1	2	3	4	5
MNF normal	174.6599	178.0621	164.062	187.081	166.5086
MNF Pathological	158.0516	156.4694	142.4638	160.9222	158.8944

Fig. 5 Variation in mean frequency of normal and pathological leg of Lateral gastrocnemius

Fig 5 shows the mean frequencies of all five subjects for normal leg and pathological leg. The MNF values ranging between 164Hz to 187 Hz for normal leg which was quite higher than the pathological leg with frequencies ranging from 142 Hz to 160Hz.The blue histogram shows subjects with normal leg, whereas, red histogram shows subject with pathological leg. It is clearly seen from the Fig. 5 that the Mean Frequency of normal leg is always more than pathological legs.

IV CONCLUSION

In this paper, 5 subjects with one leg affected were studied. All ofthem were instructed to walk on a platform of 4m. Calf muscle was studied by calculating EMG using MATLAB.

The following conclusions were drawn:

1. Out of all the muscles present in lower limb, the calf muscle was identified as the main muscle providing about 90% of the total strength.
2. Endurance strength of normal leg was less compared to pathological leg.

The present work is relevant in the field of medical science in order to design an artificial prosthetic leg.

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