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KNOWLEDGE BASED DATABASE OF MUSCLE ACTIVITY CHARACTERIZATION USING DIAGNOSTIC ELECTROMYOGRAPHY (D-EMG) SIGNAL

Syed Samser Ali, Bipasha Chakrabarti Banik, Priyanka Sarkar Das

Department of Electronics and Communication Engineering, Gargi Memorial Institute of Technology, WB

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ABSTRACT

In this paper, Diagnostic Electromyography (D-EMG) signal interpretation of human arm towards characterization of arm muscle interaction during various arm movement has been discussed. EMG signals from 4 important arm muscle (i.e. Bicepsbracci, Tricepsbracci, brachioradialis and lateral deltoids) are recorded clinically during 5 different arm movements (i.e. Extension of forearm, Flexion of elbow joint, Pronation of forearm, shoulder abduction and Wrist flexor stretch) under load condition (a load of 2 Kg& 4 Kg maintained during experimental arm movement), the recorded D-EMG signals are properly enveloped within a range of 5-100 Hz and quantized within a proper sampling frequency range to produce a knowledge based database of muscle activity. In addition, correlation of muscle activity and Power spectral density (PSD) analysis has been carried out towards muscle process discriminating during various arm action.

KEYWORDS

Knowledge Based Database, Diagnostic Electromyography (D-EMG), Arm Movement, Muscle Activity, Envelope detection, Sampling, Correlation of Muscle Activity, Power Spectral Density (PSD), Big Data.

1. INTRODUCTION

Knowledge based database towards the aim of machine learning for actuations of prosthetic arm is carrying its importance reflected with experimental study has become a major research interest in modern scenario. Analysis of surface Diagnostic-EMG (D-EMG) signal provides an effective way of understanding the muscle action during various human locomotive movements (Cohen, 2013). EMG signal recorded during human activities is a voluntary action of muscle fiber contraction and expansion which comprises of actuation of neuron potentials which creates electromagnetic field around the active locomotive muscle region, and analysis of generated electromagnetic field potential gives overview knowledge of active and inactive muscle. Raw EMG signals captured during muscle activity offers beneficial data in a particularly useless form. This data is valid only if it can be quantified. Various signal-processing techniques are applied on raw EMG Signal to achieve the meticulous and authentic EMG signal motif. These motifs are used in further research towards arm activity analysis. Arm muscle activity detection is performed by using of the EMG envelope. Excluding manual analysis of the raw EMG signal, other common methods use digitized EMG signal. Commonly, the EMG envelope (i.e. the smoothed signal obtained through low-pass filtering of the rectified EMG signal) is used as it allows simple classification and relatively simple muscle curve shape analysis. The SNR should contain the large amount of data from EMG signal as possible and less amount of noise contamination. The distortion factor of EMG signal must be as low as possible with no irrelevant filtering and distortion of signal peaks and notch filters are not recommended (Ekstrom et al., 2007).

2. METHODS

2.1 Participants

A Group of eight Bachelor of Technology (B.Tech) final year students of JIS College of Engineering including male and female within age group- 20 yrs, avg. weight- 70 $\pm$ 5 kg (male) and 50 $\pm$ 5 kg (female) participated in this research activity under the guided supervision of Dr. Biswarup Neogi, ECE dept. JIS College of Engineering. All students bared from any muscular injury blocking up the participation in drawing load task. All students participated in the activity received verbal as well as written consent prior to the activity.

2.2 EMG recording

Non-invasive non-returnable surface invigorating and recording Ag/AgCl electrodes with 0.5" X 0.5" recording area, 24" colored leads ideal for Audio Evoked Potential (AEP) and Nerve Conduction Studies (NCS) were used in pairs over the skin and parallel to the fibers of Biceps bracci, Triceps bracci, Brachioradialis and lateral deltoids muscles with an inter-electrode spacing of 0.2 m (Fig.1). Before electrode placement each team member's arm skin was smooth-shaven with a new razor, and cleaned with wet wipers (Hislop et al., 2014). Fresh EMG signal has been obtained using RMS EMG Recorder® which specifies the application of three distinguishable electrodes. One is attached with the particular muscle, the EMG signal of which is to be recorded; the other is attached to a different muscle used as a reference against the original data recorded; the remaining electrode is used as ground. EMG Electrode Conductive gel ® has been applied to the electrodes to act as a dielectric

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medium reducing noise inclusion (Konrad, 2006). The recorded EMG data is displayed on the monitor through RMS EMG EpMK2 on an amplitude vs time graph with scaling of 20ms/D on the X axis and 50mV/D on the Y axis (Konrad, 2006; Kraemer et al., 2002).

2.3 Normalization

Adaptation of all movements with visual EMG feedback was performed, followed by a 10 minutes rest period prior to MVIC performed against manually resistance for each movement (Lehman et al., 2004). Participants executed three MVIC per muscle; surface EMG signal of all muscular action were taken in random basis. Each muscular activity was held for 3-5 seconds, with one minute rest (Leslie et al., 2013). Peak EMG data recorded during drawing loads.

2.4 Linear Envelop Detection

Calculation of linear envelop of Electromyography (EMG) signal is a step required for amplitude analysis of muscular activation. Computation of linear envelop involves four sequential processes. First, signal is made free from extraneous frequency with filtering method having cut off frequency in the range of 5 to 20 Hz for low frequency components of the recorded EMG signal. The signal is then half wave rectified for proper positive peak value, prior being smoothed. Finally, High frequencies are filtered out using a low pass filtering method. Linear envelop features were taken out in the form of magnitudes and phase angle of consonants. The outcomes are displayed in the format of EMG profile.

2.5 Sampling and Quantization

Apprehending and analysis of D-EMG signal is most generally done by compute in a discrete manner, which requires transforming analog signal to digital signal using analog to digital (A/D) converter. One of the most important factors in A/D converter is sampling. Lower sampling rate can result distorted signal, such as aliasing effect, in order to avoid aliasing and other signal distortion the sampling rate must be greater than Nyquist rate according to sampling theorwm (Ricci et al., 1988). The maximum power of D-EMG signal is considered and most of the frequency components of D-EMG signal more than 500 Hz are contributed by the electrode and equipment noise or environmental interference. For D-EMG signal analysis broadly used sampling rate is 1KHz. Using highsampling rate involves high frequency components of the muscular signals taken with the surface electrodes but contemporaneously adds prosthesis controller handling and time complexity. Thus, it is advisable in signal acquisitions of EMG signal to use a lower sampling rate as much as possible (Vanderburgh et al., 2000). Quantization of sampled signal consists in expressing the analog value in digital forms or step size format, which are bounded to resolution. Magnitude of each digital part is referred to LSB. The quantization presents an approximation in the generated signal, since all the step values between two subsequent values will be represented by the same digital steps size. The effect of A/D conversion of analog D-EMG signal is then limited to signal to quantization noise ratio to a value equals the value of quantization signal to noise ratio and is equal to:

$$SNR_q = \frac{S_{max}}{V_{LSB}} \leq \frac{2^N}{1} \quad (1)$$

Where, S_{max} is the maximum amplitude of the analog signal, V_{LSB} is the value of LSB in volts and N is the number of bits.

For the signal with Gaussian distribution as an EMG signal, maximum achievable value of SNR_q is:

$$SNR_{q, dB, max} = (6N - 4.8) dB \quad (2)$$

Clearly, the chosen A/D resolution should not determine the quality of the acquired signal; on the contrary, the value of SNR_q is the ultimate quality index for a desired resolution, so efforts of keeping maximum amplitude of noise limit below 1 LSB is pointless (Waite et al., 2010).

2.6 Correlation Analysis

Figure 1: D-EMG Signal capturing using Non-invasive Disposable surface stimulating Ag/AgCl electrodes with 0.5" X 0.5" recording area, 24" colored leads ideal for Audio Evoked Potential (AEP) and Nerve Conduction Studies (NCS)

Figure 2: Digital Signal Prossesing of Muscle and Movement interdependency using raw D-EMG signal recorded (i.e. Raw Data; Envelop Detection; Sampling and Quantization; Correlation Analysis)

The diagram illustrates the proposed framework for healthcare monitoring and analytics. It begins with the 'Number of Patients (N)', which leads to the 'Data Collection Phase', 'Data Storage Phase', and 'Data Processing Phase'. The processed data is then used for 'Healthcare Monitoring and Analytics: Analysis from existing case (EMH) digital monitoring'. This phase feeds into the 'Digital Signal Processing phase', which includes 'Feature Extraction', 'Feature Selection', 'Feature Reduction', 'Feature Engineering', and 'Feature Selection'. The output of this phase is 'Healthcare Monitoring and Analytics: Analysis from existing case (EMH) digital monitoring', which leads to the 'Health and Analysis Phase' and finally the 'Application Phase'.

(1)
(2)

(1)
(2)

(1) (2)

(1) (2)

Figure 5: Muscle and Arm Movement Interdependency Decision Table

2.7 Power Spectral Density Analysis

$$X_K = \sum_{N \text{ even}} x(N) W_N^{nK} + \sum_{N \text{ odd}} x(N) W_N^{nK}$$
$$X_K = \sum_{r=0}^{N/2-1} x(2r)W_N^{2rK} + \sum_{r=0}^{N/2-1} x(2r+1)W_N^{(2r+1)K}$$

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3. RESULTS AND DISCUSSIONS

3.1 Digital Signal Processing of Muscle and Movement Interdependency Analysis

Cortical neuron potential signal capturing through D-EMG signal of voluntary muscle action during various arm movement under load condition is the first step towards signal processing analysis (Section II.B). The second step, filtering and rectification of recorded EMG signal from extraneous noise and creation of normalized envelop using moving average method towards qualitative pattern analysis (Section II.D). Since, the recorded EMG signal is analog form and its analysis through CAD tools the first step of converting the analog data into digital form using A/D convertor using proper sampling rate, sampled data is converted into digital data using the methods of quantization (Section II.E). As discussed (Section II.F) quantitative evaluation can be assessed using the correlative analysis, the CAD evaluation result obtained for correlative analysis given in Fig.2, attained result can be analyzed quantitatively as for extension of fore arm (Fig.2.a) the peak magnitude in the correlation result denotes the dependency of Biceps, Triceps, Flexor and Deltoid muscle and width of the correlation curve in time domain depicts the muscle activity time interdependency, on the similar analysis strategy considering Pronation of forearm (Fig.2.c) biceps muscle remains inactive i.e. correlation curve doesn't have any peak magnitude value and other muscle is active i.e. dependent during movement action. In similar manner each correlative graph (Fig.2.b, 2.d-e) can be examined qualitatively and qualitative overview of muscle-movement can be established.

3.2 Power Spectral Density (PSD) Data Analysis

The real time D-EMG data has been collected from the group of students for the following arm movement and its muscle interdependency. The simulation part is carried out in MATLAB platform. The power spectral density of the input EMG signal can be estimated by its periodogram where the frequency range is from 0-70 Hz and the Power per frequency is -20 to +25 dB/Hz. Various windowing technique can be used over here for the analysis of frequency of EMG Signal like Hamming Window method, Kaiser Window method etc. In our analysis frequency range (0-70 Hz) is same for all the movements and power per frequency is about 20-30 dB/Hz. But there is only one movement that is "wrist flexor stretch" where there is no power per frequency is obtained for the muscle Biceps as it is considered a slothful muscle. During a sustained isometric contraction the surface EMG signal becomes "slower", the PSD is squeezed towards lower. The PSD analysis (Section II.G and Fig.4) shows the frequency contents for the entire length of the EMG data. Another significant part of spectral analysis depends on showing how the frequency components vary with time. Qualitative assessments can be made by calculating the PSD for each segment of data and comparing them. Quantitative assessments can be made by calculating the mean frequency or the median frequency of the PSD sequentially for epochs of EMG data.

3.3 Limitations

In this present research, D-EMG processed data has been utilized as a reference for creating a knowledge based database as mentioned previously for activity during load pull variants. This research needed participants to use a controlled pulse rate, while muscle function outline could be different if participants select their pull up speed by themselves. Additionally, there may be other muscle group which might have not been taken into account for present research study but which may create differences in EMG responses during load pull. Some difference in muscle activation period between participants may have resulted from variations in the forearm length and palm diameter. Load pull activity calculated in this research needs steady forearm movement with a time period of 2 sec variation, had lapse of time been diminished more precise observation could be made, which is a constraint in this research.

4. CONCLUSIONS

Knowledge based database creation of human voluntary arm movement under load condition is a preliminary initiation towards development of biological data cloud for machine learning research leading to human prosthetics arm advancement. Present research primarily focused on creating a state of reference of movement and muscle interaction through D-EMG signal capturing, interpretations and analysis through digital signal processing methods i.e. sampling and quantization, correlation

analysis and power spectral density analysis. The preliminary outcome of the present research is the bio-signal analysis of captured D-EMG signal and a pathway leading to database of arm muscle interaction during various arm movements. On the future aspect, this research will be carried out to create a digitally established EMG signal of human arm movement and muscle interactions in Big Data format towards IOT based advancement as discussed in Fig.4 and the decision table as shown in Fig.5 would contribute towards development of futuristic electronic based physio-therapeutic systems, can be used as a reference material for human prosthetics researchers and also contribute largely in the domain of medicines i.e. identifying early features of neurodegenerative disease.

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