BIOMEDICAL ENGINEERING | RESEARCH ARTICLE

Knowledge Based database of arm-muscle and activity characterization during load pull exercise using Diagnostic Electromyography (D-EMG) Signal.

Pritam Chakraborty¹, Biswarup Neogi² and Achintya Das³

Abstract: In this paper, Diagnostic Electromyography (D-EMG) signal interpretation of human arm towards characterization of arm-muscle interaction during various arm movements has been discussed. EMG signals from four important arm muscle (i.e., Biceps bracci, Triceps bracci, brachioradialis, and lateral deltoids) are recorded clinically during five different arm movements (i.e., Extension of the 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 actions.

Subjects: Database Design & Development; Data Preparation & Mining; Biomechanics; Computer & Software Engineering

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PUBLIC INTEREST STATEMENT

To appraise a significant facet from the Diagnostic Electromyography (D-EMG) signal, this article is the keystone towards the formation of knowledge-based database of Arm-muscle and activity characterization. Evaluation of muscle activation has been carried out using correlation and power spectral density during various arm movements gives an overview knowledge of active and inactive muscle. Diagnostic Electromyography (D-EMG) signal recorded during the human locomotive movement provides an effective way of understanding the muscle instigation.

With the advent of machine learning and highly optimized algorithms, analysis of D-EMG signal during our day-to-day job brings out important acumen of human locomotion–muscle interfaces which will be beneficial for the medical practitioners to identify early topographies of neuro-generative diseases, for the physiotherapists, and also in the domain of prosthetic research.

This investigation will pave a way for Healthcare 4.0 application in physiotherapy, clinical, and also in the domain of prosthetic research.
Keywords: Knowledge-Based Database; Diagnostic Electromyography (DEM); 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 actuation of the prosthetic arm is carrying its importance reflected with experimental study has become a major research interest in the modern scenario. Analysis of surface Diagnostic-EMG (D-EMG) signal provides an effective way of understanding the muscle activity during various human locomotive movements (Andersen et al., 2006). 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 an electromagnetic field around the active locomotive muscle region, and analysis of generated electromagnetic field potential gives overview knowledge of active and inactive muscle (Norcross et al, 2010; Garcia-Vaquero et al, 2012).

Raw EMG signals captured during muscle activity offers valuable information in a particularly useless form. This information is useful only if it can be quantified. Various signal-processing methods are applied to raw EMG to achieve the accurate and actual EMG signal pattern. These patterns are used in further research towards muscle activity analysis (McGill et al, 2014).

Muscle activity detection is performed by using of the EMG envelope (De Luca et al, 1997; Williams, et al, 1999; Vanderburgh et al, 2000). Excluding manual analysis of the raw EMG signal, other common methods use digitized EMG signal There are some progressive methods such as Bayesian change-point analysis (Bolgla & Uhl, 2005) or Kalman smoother (Bull et al., 2011); however, rather simple detections are much more popular. 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 interpretation and relatively easy muscle onset and cessation detection or a more detailed curve shape analysis. The signal-to-noise ratio should contain the highest amount of information from EMG signal as the possible and the minimum amount of noise contamination. The distortion of EMG signal must be as minimal as possible with no unnecessary filtering and distortion of signal peaks and notch filters are not recommended (Burden, 2010; Cohen, 2013; 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 ± 5 kg (male), and 50 ± 5 kg (female) participated in this research activity under the guided supervision of Dr. Biswarup Neogi, ECE dept. JIS College of Engineering. All students were free from any musculoskeletal injury obstructing the participation in load-pull task (Ricci, et al, 1988; Signorile, et al, 2002; Ronai, et al, 2014). All students who participated in the activity received verbal as well as written consent prior to the activity.

2.2. EMG recording

Noninvasive Disposable surface stimulating 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 placed in pairs over the skin and parallel to the fibers of Biceps bracci, triceps bracci, brachioradialis, and lateral deltoid muscles with an inter-electrode spacing of 0.2 m (Figure 1). Before electrode placement, each team member’s arm skin was smooth-shaven with a disposable single-use razor, and vigorously cleaned with alcohol wipers until erythema attained (Ekstrom et al., 2007). Raw EMG signal has been collected 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 medium reducing noise inclusion. The recorded EMG data are displayed on the monitor through RMS EMG EpMK2 on an amplitude vs time graph with the scaling of 20 ms/D on the X-axis and 50mV/D on the Y-axis. The placements of electrodes were positioned in accordance with the recommendations of Hermens et al. (1999), Bull et al. (2011), Hibbs et al. (2011), and Waite et al. (2010), respectively. All the electrodes are placed on the participant’s right-hand dominant site, assuming motor control symmetry on both sides of the body (McGill et al., 2014).

2.3. Normalization
Alteration of all movement with visual EMG feedback was carried out, followed by a 5 min rest period prior to MVIC performed against manual resistance for each movement (Eldridge et al., 2006; Rouffet, et al, 2008). Participants performed three MVIC per muscle; surface EMG of all muscle activity was measured in randomized order. Each muscle activity was held for 5 s, with 1-min rest between each repetition (Fleiss, 2011). Peak EMG data recorded during load tests during pull-up variants were normalized utilizing only the positive values of the recorded data (Fleiss, 2011; Floyd, 2012; Hermens et al., 1999)

2.4. Linear envelop detection
Calculation of linear envelop of Electromyography (EMG) signal is a step required for amplitude analysis of muscular activation. The computation of linear envelop involves four sequential processes. First, the signal is made free from the extraneous frequency with a bandpass filter with a cut-off frequency within the range of 5 to 20 Hz for low-frequency components of the recorded EMG signal. The signal is then half-wave rectified for absolute positive peak value, prior to being smoothed with moving average (MA). Finally, high frequencies constituents within the range of 200 Hz to 1 kHz are filtered out using a low-pass filter. Pattern analysis of the extracted envelop requires the use of qualitative parameters to represent the individual patterns and then performs the grouping procedures on these parameters. Linear envelop features were extracted in the form of magnitudes and phase angle of harmonics. The results are presented in the format of an EMG profile.

2.5. Sampling and quantization
Apprehending and analysis of the D-EMG signal is most commonly done digitally by computer, which requires transforming the analog signal into a digital signal using an analog to digital (A/D) converter. One of the most important factors in the A/D converter is a sampling. A slow sampling rate can result in the distortion of the signal, such as aliasing, in order to avoid aliasing and other signal distortion the sampling rate must be greater than Nyquist rate (Burden & Bartlett, 1999).
The major power of the D-EMG signal is accounted for by harmonics up to 400–500 Hz range and most of the frequency components of the D-EMG signal more than 500 Hz is contributed by the electrode and equipment noise or environmental interference. Thus, for D-EMG signal analysis broadly used sampling rate is 1 kHz. Utilizing a high sampling rate involves high-frequency components of the myoelectric signals captured with the surface electrodes but concurrently add prosthesis controller processing and time complexity (Youdas et al., 2008; 2010). Thus, it is desirable in signal acquisitions of EMG signal to use a low sampling rate without compromising controller performance (Hibbs et al., 2011). Quantization of the sampled signal consists of expressing the analog value in digital forms or steps, which has limited resolution. The amplitude of each digital form is referred to as the least significant bit or LSB. The quantization presents an approximation in the reconstructed signal, since all the values of the between two subsequent values will be represented by the same digital steps, it can be modeled as an additive noise that is added to the signal in order to obtain digital representation. The effect of A/D conversion of analog D-EMG signal is then limited to signal-to-noise ratio to a value equals the value of quantization signal-to-noise ratio, for a signal with uniform amplitude distribution, equals:

$$SNR_q = \frac{S_{\text{max}}}{V_{\text{LSB}}} \leq 2^{N}$$

(1)

Where $S_{\text{max}}$ is the maximum amplitude of the signal of the fed into A/D, $V_{\text{LSB}}$ is the value of LSB in volts and $N$ is the number of bits.

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

$$SNR_{\text{d.B}.\text{max}} = (6N - 4.8)\text{dB}$$

(2)

Clearly, the chosen A/D resolution should not detriment the quality of the acquired signal; on the contrary, the value of $SNR_q$ is the ultimate performance limit for the desired resolution; thus, efforts of keeping the maximum amplitude of analog noise limit below 1 LSB is pointless (Hislop et al., 2014; Konrad, 2006)

2.6. Correlation analysis
A quantitative evaluation of the relationship between human movement and muscle involved in its motion can be estimated utilizing correlative analysis. Since the muscle movement is related to the cortical neuron potential signal activities are small as compared to EMG activities; they cannot be identified by visualized inspection of raw data, even if they might occur in close time relation (Kraemer et al., 2002; Lehman et al., 2004)

2.7. Power spectral density analysis
A common process for evaluating electromyography (EMG) data is the Power Spectral Density (PSD). This frequency-domain technique splits the EMG signal into a fixed number of time periods and runs the Power Spectral Density transformation on each slot. The usable energy of the signal is limited to the 0 to 500 Hz frequency range, with the dominant energy being in the 50–150 Hz range. Usable signals are those with energy above the electrical noise level. The frequency spectrum of EMG signals must be obtained in order to investigate the frequency domain behavior and characterize the frequency components of EMG signals. For this reason, using advanced digital signal-processing methods should be beneficial. Fast Fourier Transform (FFT) method was used to obtain the frequency spectrum of the EMG signal. Also, digital filters are used to take several frequency components. In order to extract the desired components and parameters from frequency domain behavior, a qualified FFT process should be applied to the EMG signal. FFT is another method for Discrete Fourier Transform. While it produces the same result as the other approaches, in addition FFT becomes more effective reducing the computation time by hundreds.
In complex notation, the time and frequency domains each contains one signal made up of N complex points. Each of these complex points is composed of two numbers, the real part, and the imaginary part. In other words, each complex variable holds two numbers. Two complex variables are multiplied; the four individual components must be combined to form the two components of the product. Assuming that N is an even integer, x(n) array can be divided into two arrays that have N/2 length.

\[ X_K = \sum_{\text{Even}} x(n)W_N^{nk} + \sum_{\text{Odd}} x(n)W_N^{nk} \]

For \( n = 2r \) and \( n = 2r + 1 \) Separation Process can be realized.

\[ X_K = \sum_{r=0}^{N-2} x(2r)W_N^{2rk} + \sum_{r=0}^{N-2} x(2r + 1)W_N^{2(r+1)k} \]

The FFT operates by decomposing an N point time-domain signal into N time-domain signals each Composed of a single point. The second step is to calculate the N frequency spectra corresponding to these N time domain signals. Lastly, the N spectra are synthesized into a single frequency spectrum (Leslie & Comfort, 2013; McGill et al., 2014)

3. Results And discussions

3.1. Digital signal processing of muscle and movement interdependency analysis

Cortical neuron potential signal capturing through the D-EMG signal of voluntary muscle action during various arm movements 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 the 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 Figure 2, attained result can be analyzed quantitatively as for extension of forearm (Figure 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 (Figure 2(c)) biceps muscle remains inactive, i.e., correlation curve does not have any peak magnitude value and other muscle is active, i.e., dependent during movement action. In similar manner, each correlative graph (Figure 2(b,d–e)), figure 3(a,b) examined qualitatively and a qualitative overview of muscle-movement can be established.

3.2. Power spectral density (PSD) DATA ANALYSIS

The real-time D-EMG data have been collected from the group of students for the following arm movement and its muscle interdependency. The simulation part is carried out in the MATLAB platform. The power spectral density of the input EMG signal can be estimated by its periodogram where the frequency range is from 0 to 70 Hz and the Power per frequency is −20 to +25 dB/Hz. Various windowing techniques can be used over here for the analysis of the frequency of EMG Signal like the Hamming Window method, Kaiser Window method, etc. In our analysis frequency range (0–70 Hz) is the 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 an inactive muscle. During a sustained isometric contraction the surface EMG signal becomes
“slower,” the power spectral density is compressed toward lower frequencies, and spectral variables (MNF, MDF) decrease. The decrease of these variables reflects a decrease of muscle fiber conduction velocity and changes of other variables (such as active motor unit pool, degree of synchronization, etc.).

The PSD analysis (Section II. G and Figure 4) summarizes the frequency components for the entire length of the EMG data. Another important part of spectral analysis relies on studying 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 have been utilized as a reference for creating a knowledge-based database as mentioned previously for investing dynamic muscle activity during
load-pull variants; however, specific recommendations were followed in order to reduce inter-individual discrepancy and increased dependability as reported previously by Ekstrom et al. (2007); Hislop et al. (2014); Konrad (2006). This research required participants to use a controlled pulse rate, while muscle activity outline could be different if participants self-select their pull-up speed. Additionally, there may be other muscle group which might have not been taken into account for the present study but which may reveal greater differences in EMG responses during load-pull variants. Some variations in muscle activation between participants may have resulted from differences in the forearm length and palm diameter. Load pull activity studied in this research requires steady forearm movement with a time span of 2 sec variation, had the time span been reduced more precise observation could be made, which is a limitation in this study.
4. Conclusions

Knowledge-based database creation of human voluntary arm movement under load condition is a preliminary initiation towards the development of biological data cloud for machine learning research leading to human prosthetic arm advancement. Present research primarily has focussed 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 a 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 Figure 4 and the decision table as shown in Fig.5 would contribute towards the development of futuristic electronic-based physio-therapeutic systems, can be used as a reference material for human prosthetic researchers, and also contribute largely in the domain of medicines, i.e., identifying early features of neurodegenerative disease.

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