Features Extraction of Electromyography Signals in Time Domain on Biceps Brachii Muscle

Wan Mohd Bukhari Wan Daud, Abu Bakar Yahya, Chong Shin Horng, Mohamad Fani Sulaima and Rubita Sudirman

***Abstract*—Electromyography (EMG) is widely used in various fields to investigate the muscular activities. Since EMG signals contain a wealth of information about muscle functions, there are many approaches in analyzing the EMG signals. It is important to know the features that can be extracting from the EMG signal. The ideal feature is important for the achievement in EMG analysis. Hence, the objective of this paper is to evaluate the features extraction of time domain from the EMG signal. The experiment was setup according to surface electromyography for noninvasive assessment of muscle (SENIAM). The recorded data was analyzed in time domain to get the features. Based on the analysis, three features have been considered based on statistical features. The features was then been evaluate by getting the percentage error of each feature. The less percentage error determines the ideal feature. The results shows that the extracted features of the EMG signals in time domain can be implement in signal classification. These findings could be integrated to design a signal classification based on the features extraction.**

***Index Terms*—biceps brachii, electromyography (EMG), features extraction, time domain.**

I. Introduction

Human bioelectrical signals are extensively studied and applied in various clinical and psychophysiological researches. However, the intention of using these signals in the field of information technology is newer. Bioelectrical signal means an electrical signal obtained from any organ that exhibits a physical variable of interest. This signal is commonly a function of time and is definable in terms of its amplitude, frequency and phase [1]. An Electromyography (EMG) signal is a biomedical signal that measures electrical currents generated by the skeletal muscles during its contraction exhibiting neuromuscular activities. Understanding EMG signals involves the understanding of the skeletal muscles and the approach they generated bioelectrical signals. It also involves the consideration of the specific mechanisms and phenomena that affect the signals. EMG is a complex signal affected by many aspects such as physiological and anatomical properties and characteristics of instrumentation. It is distinct from one person to another. The EMG signals are helpful, due to real-time monitoring for these signals. It includes real-time information about the electrical activity of a particular muscle which is related to muscle force. The relationship between muscle force and EMG has been reviewed during isometric contractions and dynamic contractions. Many ways of modeling for computing muscle force have been suggested; but these models cannot be validated due to insufficiency of an accurate experimental procedures to compute the muscle force [2], [3]. Recently, muscle coordination is essentially reviewed from surface EMG activity.

The noninvasive measurement for biosignals is important due to their abilities in supporting many critical biomedical applications for monitoring, diagnostics and therapies. Surface EMG (sEMG) is one of the noninvasive measurement which means a procedure that do not involve tools that break the skin or physically enter the body. In other words, sEMG is a result in space and time of electrical activities with muscles under the skin. The applications of sEMG signal are including in rehabilitation and assistive technology. The most important application of sEMG signal in these fields is to control the prosthesis or other assistive equipments by applying the different patterns of sEMG signal. The amplitude of the sEMG signal depends on the muscle types and conditions during the observation process and it is about ranges of µV to mV.

There are various types of electrodes that being used to measure EMG signals. The core classes are needle electrodes, fine-wire electrodes and surface electrodes. The electrode selection is depending on the purpose of the experiment to be carried out. For invasive application, needle electrodes and fine-wire electrodes are used. While the surface electrodes are used for noninvasive application. The usage of surface electrodes was recommended by the Surface Electromyography for the Non-Invasive Assessment of Muscles (SENIAM) project. The SENIAM project is a European concerted action in the Biomedical Health and Research Program (BIOMED II) of the European Union. In fact, in comparison with invasive based methods, the surface electrodes produces free of discomfort to the subject and gives only minimal risk of infection.

In the study carried out by P. Laferriere et al. [4], they used surface electrodes to obtain the sEMG signals on the skin's surface, above the desired muscle. The usage of conventional surface electrode, silver/silver chloride (Ag/AgCl) electrode, gives quality sEMG signals but has some problems. The application of Ag/AgCl electrodes need to use electrolyte gel that may cause the skin irritation and allergies. The electrolyte

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gel which is used to increase the SNR by reducing the impedance of the electrodes may dries up with time and leading to a drastic reduce of the signal quality. The suggested dimension of electrode for EMG analysis by SENIAM is 10 mm diameter.

II. Experiment and Data Acquisition

A. Subjects

Two normal and healthy male subjects were participated in this study. The subjects were selected according to dominant hand; right-handed, and weight; above 60 kg. The subjects are voluntary and have signed a consent form before the experiment is conducted.

B. System Design

This experiment uses basic system for acquiring biosignal. Starting from electrodes, data acquisition until signal processing was designed in order to give feedback to user. Fig. 1 below shows the block diagram of designed system in this experiment.

The system design includes the sEMG self-adhesive silver-silver-chloride (Ag/AgCl) electrodes that used as transducer to capture the EMG voltage signal. It was attached to the specific muscles of the forearm. Ag/AgCl electrodes are chosen due to their half-cell potential is closer to zero compared to other types such as silicon rubber electrodes [5]. Three Ag/AgCl electrodes were used in this experiment for a subject. Independent measurement can be obtained from the hand movement without moving the shoulder.

The captured EMG signal from the surface electrodes then being digitized by the sEMG data acquisition system; TeleMyo 2400T G2 (Noraxon, USA Inc.). The sEMG data acquisition system is used to record EMG signals from the subjects. The EMG signals were obtained by using the TeleMyo 2400T G2 Transmitter, which sends the signals via wireless transmission to the TeleMyo PC-Interface Receiver that forward the data via USB to the computer at a sampling rate of 1500 samples per second. A computer was used as digital signal processing system that do the process in this experiment; which is digital filtering and features extraction.

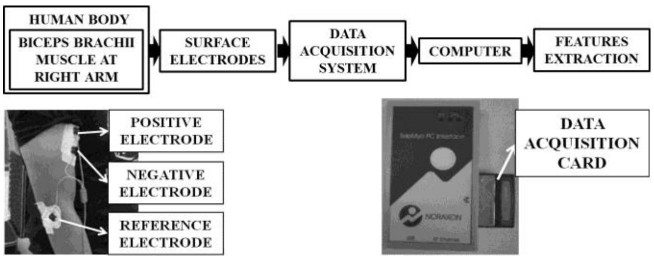


Fig. 1. Block diagram of the system.

C. Experimental Procedures

Experiment starts by cleaning the subject's skin surface on right arm's biceps brachii. It is purposely to reduce the skin impedance. After cleaning the skin surface, the skin impedance then measured. If the cleaning steps were done properly, the skin typically gets a light red color. This indicates good skin impedance condition. To verify it, the Ohm-resistance between the electrode pair can be measured. This experiment is considering the skin impedance. The value of the skin impedance that can be used for the measurement can be classified in Table I. The skin preparation procedures are important to ensure the quality of an EMG measurement. The quality of an EMG measurement strongly depends on a proper skin preparation and electrode positioning. The aim of skin preparation is to get stable electrode contact and low skin impedance.

Fig. 2 shows the overall work for the proposed study. The EMG signal were recorded using three electrodes; two electrodes for recording the EMG signal and one electrode as reference electrode, which were placed on the subject's right forearm biceps brachii muscles of healthy subject. The placement of the sEMG electrodes on the skin is according to surface Electromyography for the non-invasive assessment of muscles (SENIAM). This experiment was done in quite room to minimize the noise and can get better signals. The subject was leaning against the wall to get a straight and upright posture as shown in Fig. 2. Data for this experiment are recorded continuously. Starting from rest condition, lifted hand without load, lifted hand with 3 kg load and 5 kg load. These data will be used for estimating the average of muscle's force at biceps brachii muscle.

TABLE I: Skin Impedance Reference for Measurement

Impedance Range (kΩ)	Recommendation
1 – 5	Very good condition
5 – 10	Good and recommended if feasible
10 – 30	Acceptable for easy condition
30 – 50	Less good, attention is needed
>50	Should be avoided or requires a second cleaning run

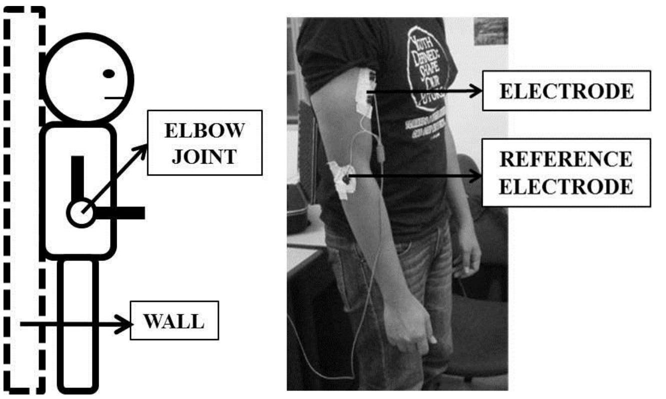


Fig. 2: The experiment setup.

The subject then supervised by an instructor who gave instructions on how to lift their hand without load and with a dumbbell load of 3 kg and 5 kg. 5 kg is a capable maximum load that a normal and healthy person, including male and female, can lift by using a dumbbell on single hand. Right-handed subject was chosen for this experiment. During the experiment, the right hand of the subject was lift from $\theta_E = 0^o$ to $\theta_E = 145^o$; refer at the elbow joint. The subject lifted hand with distinct weights starting from no load to heavier weight. 145^o is the maximum range of flexion at the elbow joint [6]. Subjects lift the load from $\theta_E = 0^o$ and hold at $\theta_E = 145^o$ for 10 seconds; then lowering back the load to $\theta_E = 0^o$ as shown in Fig. 3. Holding the load for period of 10 seconds is function as indicator to make sure that the EMG signals are reaching its maximum amplitude. During the experiment, the subject should not move their shoulder. They only lift the load by using their hand, while the load is placed at the hand. Fig. 4 shows the position of the hand during flexion. Subjects had 5 minutes of rest during exchange from one weight to another in order to avoid muscles fatigue.

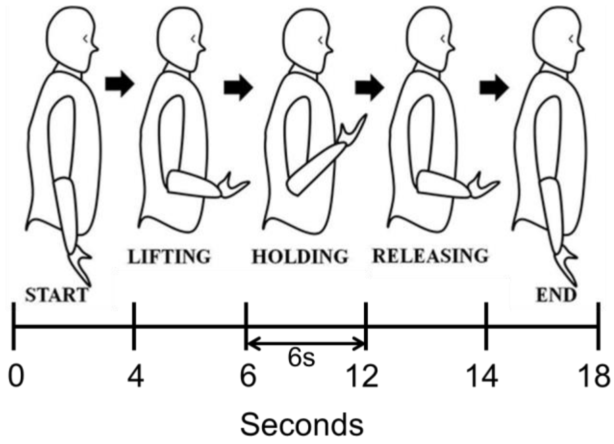


Fig. 3: The movement of the subject.

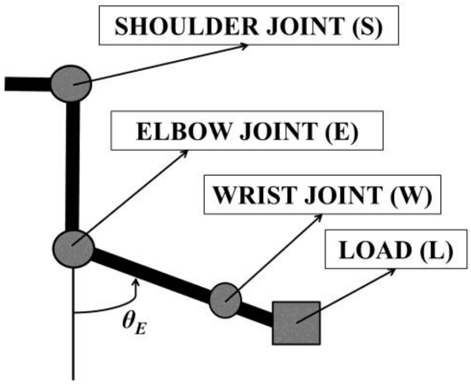


Fig. 4: The position of subject's hand during flexion.

D. *Time Domain Features*

Features in time domain have been widely used in medical and engineering practices and researches. Time domain features are used in signal classification due to its easy and quick implementation. Furthermore, it does not need any transformation, which the features are calculated based on raw EMG time series. Non-stationary property of EMG signal, changing in statistical properties over time has come to be disadvantage for the features in time domain, but time domain features assume the data as a stationary signal [7]. Moreover, much interference that is acquired through the recording because of their calculations is based on the EMG signal amplitude. However, compared to frequency domain and time-frequency domain, time domain features have been widely used because of their performances of signal classification in low noise environments and their lower computational complexity [8]. Three time domain features have been proposed in this study through extensively review the literatures.

III. Methodology

A. *Features Extraction Stage*

The information of statistical features extraction for the EMG signals were been done in MATLAB R2011a. Three statistical features from time domain are used in evaluation. Time domain features are measured as a function of time. It is popular for implementation on EMG signal features extraction due to its implementation and computation simplicity. Time domain features can be implemented in real-time. It usually used for detecting muscle contraction, muscle activity and onset detection. The three statistical features based on time domain are described as follows.

1) *Maximum Amplitude*

Maximum amplitude (MAX) is defined as the peak amplitude of a signal. It is often used in areas where the measureand is a signal that is not sinusoidal, which is the signal that swings above and below a zero value.

2) *Standard Deviation*

Standard deviation (SD) measures the spread of data from the mean. In signal processing, SD represents noise and other interference. It is used in comparison to the mean. This leads to the term: signal-to-noise ratio (SNR), which is equal to the mean divided by the standard deviation. Better data means a higher value for the SNR.

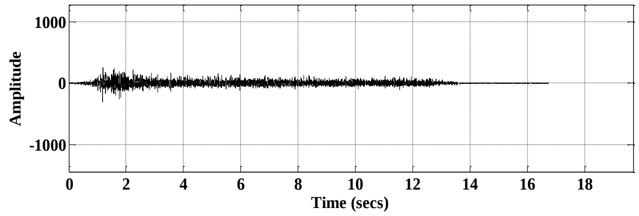
3) *Root Mean Square*

Root mean square (RMS) is another feature that popular in EMG signal analysis. RMS is defined as the square root of the mean over time of the square of the vertical distance of the graph from the rest state. related to the constant force and non-fatiguing contraction of the muscle. In most cases, it is similar to standard deviation method.

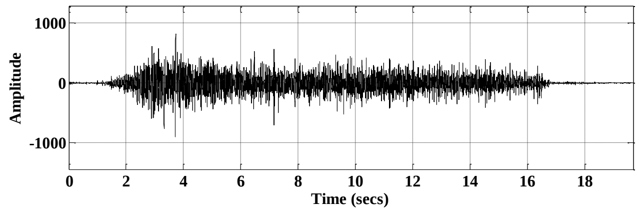
IV. Results and Discussion

A. *Characteristics of EMG Signal*

The EMG data in this study are measured during lifting their hand without load and with a dumbbell load of 3 kg and 5 kg. Fig. 5 shows the raw EMG signals during the experiment. As can be observed in Fig. 5, when the muscle contraction was maintained for a long period, the EMG signal amplitude was decreased. It proves that the EMG signal is a non-stationary signal which the frequency of the signal changes over time. Furthermore, the relationship between changing in force during muscle contraction and increasing of load can be observed in Fig. 5. The amplitudes of EMG signals are increasing as the load increases. The amplitudes of EMG signals for 5 kg load as shown in Fig. 5(c) are higher than 3 kg. While the amplitudes of EMG signals for 3 kg load as shown in Fig. 5(b) are higher than signal obtain from lifting hand without load. The amplitudes of EMG signals for no load have been selected as the reference amplitudes of EMG signals in this experiment. Fig. 5 shows that the EMG signals get the maximum amplitude at the early stage of the recorded signal. It shows that the muscle contraction is high when the subject starts to lifting the load. While the EMG signal amplitude were decreasing at the last stage of the recorded signal because the subject is lowering down the load in order to release the load. Furthermore, the subjects usually do not provide the accurate movement of lifting the load within 10 seconds for the movement which have much dynamic motion.



(a)



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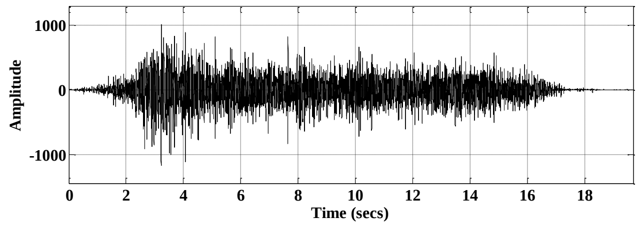

(c)

Fig. 5: Raw EMG signals for load of: (a) 1 kg, (b) 3 kg, (c) 5 kg.

B. *Assessing EMG Features*

The EMG signals were analyzed in time domain to get the features. Overall three time domain features were selected and analyzed from biceps brachii muscle for load lifting. Table II shows the average value of time domain features for three different loads that obtained from the EMG signals. As can be observed in Table II, the statistical features for the EMG signal is verify for each load. Furthermore, the statistical features were increase when the load increases. The maximum amplitude of the EMG signals is increasing as the load increases. This situation occurs due to more force needed to lift the load when the load increases. From Fig. 6, we can see that the relationship between change in load and the time domain features. As overall, the value of the features is increase due to increasing of the EMG signal amplitude according to increasing weight of load. The results show that the features are different between different loads. It can be used to classify the EMG signal according to the time domain features and weight of loads.

The percentage error of the selected statistical features then was calculated for each feature. Less percentage error determine the best chosen feature. The three time domain features; maximum amplitude, standard deviation and root mean square, were evaluated to get the best chosen feature. Table III shows the percentage error of the time domain features for the three different load; no load, 3 kg and 5 kg. SD shows the lowest percentage of error from the three different loads. It then was choose as the best feature compared with the other selected time domain features. While the RMS and MAV also can be used with SD to get a useful time domain features.

TABLE II: AVERAGE VALUE OF TIME DOMAIN FEATURES FOR THREE DIFFERENT LOADS

Load	Maximum amplitude, MAX (μV)	Standard deviation, SD (μV)	Root mean square, RMS (μV)
0 kg	686	67	485
3 kg	1594	146	1127
5 kg	2201	221	1556

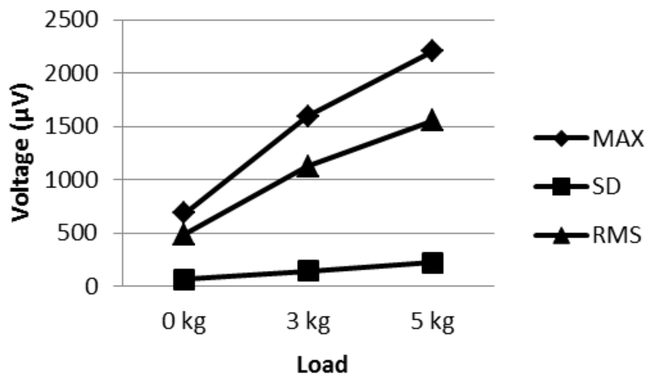

Fig. 6: Relationship of time domain features with load.

TABLE III: PERCENTAGE ERROR OF TIME DOMAIN FEATURES FOR THREE DIFFERENT LOADS

Load	Maximum amplitude, MAX	Standard deviation, SD	Root mean square, RMS
0 kg	26.2	9.3	26.2
3 kg	18.6	14.8	18.6
5 kg	4.1	10.9	4.1

V. CONCLUSION

This study is proposed and targeted to researchers to look in details of the features that can be extracting from the EMG signal within hand-lifting three different loads for better interpretation of EMG signals analysis on time domain. There are three features have been extracting from the EMG signals. The experiments demonstrate that the ideal feature can be obtain by calculate the percentage error for each feature. From the calculated percentage error, SD has the best overall performance. RMS and MAV are the better ones that can be used with SD for a useful feature vector. These findings could be integrated to design a signal classification based on the features extraction.

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