Classification of EMG Signal Based on Time Domain and Frequency Domain Features

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Abstract—**Electromyography (EMG) is widely used in controlling the signal in manipulating the robot assisted rehabilitation. In order to manipulate a more accurate robot assisted, the feature extraction and selection were equally important. This study evaluated the performance of time domain (TD) and frequency domain (FD) features in discriminating EMG signal. To investigate the features performance, the linear discriminate analysis (LDA) was introduced. The present study showed that the FD features achieved the highest accuracy of 91.34% in LDA. The results were verified by LDA classifier and FD features showed best classification performance in EMG signal classification application.**

Index Terms—**Electromyography (EMG), time domain (TD), frequency domain (FD) and linear discriminant analysis (LDA)**

I. INTRODUCTION

World Health Organization (WHO) indicated stroke had become threatening and bring 6.24 million of death to the world in 2015. Majority of stroke survivors faced long term disabilities of upper limb function [1]. Therefore, rehabilitation is required for stroke patients in order to regain their limb abilities. Today, electromyography (EMG) is widespread and widely used in rehabilitation.

EMG involved the analysis of the electrical activity of the muscle when there is muscle contraction [2]. Previous study stated most of researcher make use of surface EMG (sEMG) to evaluate the muscle performance [3]–[5]. Recently, researcher focused on the feature extraction of EMG signal [6], [7]. Feature extraction is a method to extract the useful information from surface EMG and reduce the presence of artifact. In addition, previous studies showed that the feature selection was important in achieve higher classification accuracy in EMG pattern recognition [6], [7].

The purpose of this paper is to investigate the performance of features extracted from EMG signal. This study compared the performance of time domain (TD) and frequency domain (FD) features. TD features were simple and efficient in EMG pattern recognition [6], [8]. On the other hand, FD features were used to estimate the EMG power spectrum in frequency form [5], [9]. To evaluate the feature performance, linear discriminant analysis (LDA) is use to classify the EMG pattern. Previous studies indicated the highest classification, illustrated the best feature performance in discriminating EMG signal [10]–[12].

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II. METHODOLOGY

Data Collection

Ten subjects, 8 males and 2 females, aged between 23 to 47 years were participating in the data acquisition. Subjects were right-handed and in healthy condition. Additionally, subjects have no history of accident on dominant hand. At the beginning of the experiment, there is a pre-experiment. Subjects' hair was removed in order to reduce the presence of noise. Then, the BD alcohol swab of 70% isorophyl alcohol was used to clean the surface of the skin. The Shimmer EMG sensor was used in data acquisitions. Additionally, Shimmer EMG sensor is a small and wearable device. Shimmer EMG device configuration was followed shimmer manual guideline. The gain of 12 was used and the current supply was set as 6uA. Besides, the sampling frequency was set as 512Hz with resolution of 16 bits. A high pass filter with 5Hz cut-off frequency was implemented.

The flexor carpi radialis (ch1) and flexor pollicis longus (ch2) were selected to evaluate multiple hand movement with two reference electrodes at the elbow. The anatomy of selected muscle was shown in Fig. 1. Then, the Ag/AgCL, 30 mm diameter EMG electrodes were placed on the selected muscles. The electrode placement was referring to Non-Invasive Assessment of Muscle (SENIAM) guideline. The distance between electrode-pairs is set as 20mm.

In the experiment, subjects were required to sit on the chair comfortable with hand in neutral position. Then, subjects performed six hand movement's task including thumb extension (TE), thumb flexion (TF), index finger curl (FI), middle finger curl (FM), ring finger curl (FR) and pinkie finger curl (FL) as shown in Fig. 2. These movements were followed by the FlintRehab Exercise guideline [13].

Each hand movement is maintained for 5 second and repeated for 10 times. The rest period of 3 second was introduced between each repetition. After recording, 20 EMG data were saved. In turn, subjects were required to take 1-minute rest before proceeding with next movement. This experimental setup was applied to prevent the muscle fatigue. Finally, 20 EMG signal with duration of 5 seconds were collected for each hand movement. In addition, the rest states were removed before applying the feature extraction.

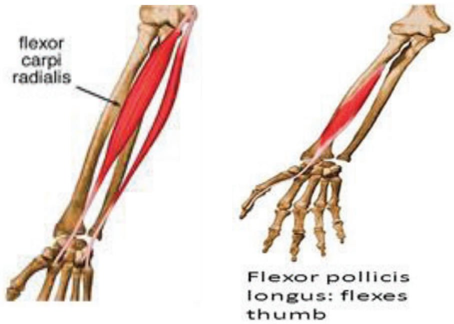

Fig. 1. Anatomy of selected muscle [5].

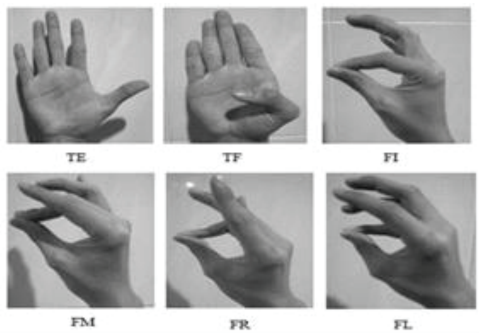

Fig. 2. Hand movement task.

A. Time Domain (TD) Feature

Figures, The time domain (TD) feature is the feature extracted from EMG signal in time representation [6]. TD features such as mean absolute value (MAV), root mean square (RMS) and wavelength (WL) were most popular in EMG pattern recognition due to high processing speed in classification. MAV is defined as the average of total absolute value of EMG signal [6], [14]. It can be calculated as:

$$MAV = \frac{1}{N}\sum_{i=1}^{N}|x_i| \tag{1}$$

RMS is the amplitude modulated Gaussian random process related to muscle force and contraction [6], [15]. It can be defined as:

$$RMS = \sqrt{\frac{1}{N}\sum_{i=1}^{N}x_i^2} \tag{2}$$

WL is an improvement of integrated EMG feature. Besides, WL is also defined as the cumulative length of waveform over the segment [6], [16]. It can be represented as:

$$WL = \sum_{i=1}^{N-1} | x_{i+1} - x_i | \qquad (3)$$

B. Frequency Domain (FD) Feature

References Frequency domain feature illustrated the EMG signal power spectrum density (PSD) in frequency representation [6]. FD features such as the mean frequency (MNF), median frequency (MDF) and frequency ratio (FR) were required more computed time as compared to TD features. In addition, FD features commonly used in muscle fatigue and muscle force estimation [5]. The MNF is the average frequency at which the sum of product of the EMG power spectrum and the frequency divided by total [5], [6]. It can be expressed as:

$$MNP = \sum_{j=1}^{M} P_j / M \qquad (4)$$

where P_j is the power spectrum and M is the length of PSD. The MDF is the frequency at which the EMG power spectrum is divided equally into two regions [5], [6]. It can be represented as:

$$MDF = \frac{1}{2}\sum_{j=1}^{M} P_j \qquad (5)$$

The FR is designed to distinguish the difference between contraction and relaxation of muscle in frequency representation [6]. It can be calculated as:

$$FR = \sum_{j-LLC}^{ULC} P_j \Big/ \sum_{LHC}^{UHC} P_j \qquad (6)$$

where *ULC* and *LLC* are the upper and lower cutoff frequency at low frequency band and *UHC* and *LHC* are the upper and lower cutoff frequency at high frequency band.

C. Linear Discriminant Analysis (LDA)

In this work, the training data set with 10 repetitions of each hand movement totaling 1200 EMG signals was computed. This study compared TD features and FD features to evaluate the features performance. The classier, LDA was utilized to classify the EMG pattern based on six classes. Linear discriminant analysis (LDA) is one of the robust classifier and it is good in reducing the dimensionality of features without separating the classes [17]. Meanwhile, LDA Previous studies indicated LDA was simple and it showed high classification performance [6], [17], [18]. The LDA was performed by using a 10-fold cross validation in classification. All the features were separated into 10 parts and each part takes turns to test. At the same time, the remainder used for training

RESULTS AND DISCUSSION

The sample raw EMG signal collected from channel 1 with six hand movements were illustrated in Fig. 3. In short, six hand movements generated different amplitude shape of EMG signal according to the type of hand movement. In order to perform frequency domain feature extraction, the Fast Fourier Transform (FFT) was utilized to represent the EMG signal in frequency and power form. In Fig. 4., the sample FFT of TF from one subject was presented.

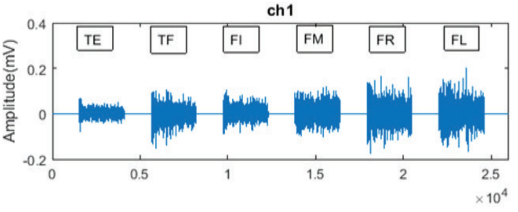

Fig. 3. Raw EMG signal from ch1 from a subject

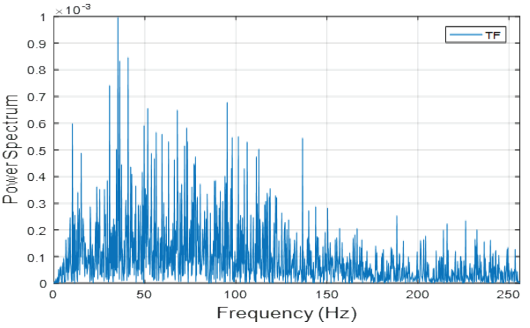

Fig. 4. Fast Fourier Transform of TF from ch1 of a subject

A. Performance Evaluation

Fig. 5. illustrates the mean classification accuracy of ten subjects. LDA result demonstrated that the FD features obtain the

highest classification accuracy of 91.34% as compared to TD features, 87.17%. In addition, the result indicated FD features in discriminating the hand movements were more accurate compared to TD features. The difference can be easily compared in TABLE I and TABLE II. TABLE I and TABLE II illustrate the confusion matrix of TD and FD features across ten subjects. As seen in Table 1-2, the TF shows the class-wise accuracy of 78% in TD feature which is less than 80%. Lower classification accuracy badly affected the performance of prosthetic system. Therefore, FD features are more suitable in classifying different hand movement. However, the number of features is still not sufficient in implementing real-time prosthetic control system. In future, the useful technique is required in rehabilitation purpose.

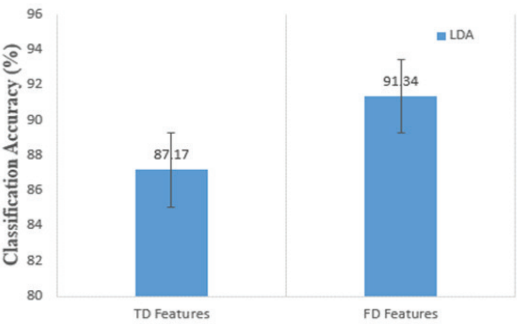

Fig. 5. Mean classification accuracy across ten subjects

TABLE 1. CONFUSION MATRIX OF TD FEATURES

	TE	TF	FI	FM	FR	FL
TE	87%	4%	4%	0%	0%	5%
TF	6%	78%	5%	0%	2%	9%
FI	2%	7%	84%	4%	1%	2%
FM	3%	3%	1%	90%	0%	3%
FR	0%	0%	3%	0%	96%	1%
FL	4%	3%	0%	2%	3%	88%

TABLE II. CONFUSION MATRIX OF FD FEATURES

	TE	TF	FI	FM	FR	FL
TE	87%	6%	3%	0%	0%	4%
TF	9%	85%	2%	1%	0%	3%
FI	3%	2%	93%	0%	0%	4%
FM	1%	0%	0%	95%	0%	2%
FR	0%	0%	1%	0%	99%	0%
FL	1%	3%	3%	2%	2%	89%

CONCLUSION

Hand movement identification required higher classification accuracy for robot assisted hand to function accurately. The feature extraction was done on EMG signal to classify hand movement. This paper presented the features performance of TD features and FD features. The experiment results showed that FD features have significantly increased classification accuracy as compared to TD features. The advantage of FD features is more appropriate to the prosthetic controlled system in rehabilitation.

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