Evaluation of EMG Feature Extraction for Movement Control of Upper Limb Prostheses Based on Class Separation Index

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Abstract— **To control of the upper-limb prostheses based on surface electromyography (EMG) movement actions, the first and the most significant step is an extraction of the efficient features. In this paper, an evaluation of various existed EMG features based on time and frequency domains is proposed by using a statistical criterion method, namely RES index, the ratio of the Euclidean distance to the standard deviation. The RES index can response the distance between movement scatter groups and directly address the variation of feature in the same group. Moreover, the evaluation of EMG features based on the statistical index does not depend on the classifier types. The EMG signals recorded from ten subjects were employed with seven upper-limb movements and eight muscle positions. Fifteen features that have been widely used to classify the EMG signals were tested with three real-time window size functions including 256, 128, and 64 samples. From the experimental results, Willison amplitude (WAMP) with threshold value 0.025 volts shows the best performance in class separation compared to the other features. Waveform length (WL) and root mean square are useful augmenting features. Two efficient features, i.e., WAMP and WL, are suggested to use as a feature vector for the EMG recognition system. It will be obtained the high classification accuracy and can be reaching for the real-time control system. Moreover, the effect of window-size functions is dependent on the type of features.**

Keywords— **Electromyography (EMG) signal, feature extraction, feature selection, cluster index, prosthesis.**

I. INTRODUCTION

In recent, surface electromyography (EMG) signal is widely used in many engineering and clinical applications. It contains lots of information from the muscles. However, it is not contained only the useful information but it also includes a variety of noises and interferences. Thus this will be lead to difficulty in the analysis of the EMG signal. Generally, in order to design an EMG recognition system, there are two main issues that should be carefully selected including feature selection and classifier design. In this study, we have been interested in the first issue. The feature selection can be implemented based on two criterions: measure of classification accuracy obtained from the classifier and measure of discrimination in feature space using the statistical index [1]. However, the first criterion has a major disadvantage that the evaluation of the EMG features depend on the classifier types, but the second criterion, the statistical index is not problematic in this way and it tries to quantify the suitableness of the feature space [2]. From the literatures, there are many existed statistical indexes for evaluation of the EMG features such as Davies-Bouldin index [1-4], scattering index [4], Fishers linear discriminate index [5], Bhattacharyya distance [6], and fuzzy-entropy-based feature evaluation index [7]. Moreover, in our previous work, we proposed a statistical index, namely the ratio of Euclidean distance and standard deviation (RES index) [8]. The most significant advantage of the proposed index is that it is simple to be implemented and computed, and the experimental result showed that this index offered the same trend with the evaluation by using an efficient classifier, namely support vector machine. However, in our previous work, the EMG signals were assumed as a short transient signal (short dynamic movement) that is only 256-ms data after the trigger or onset activity was used as a representative action EMG signal [8]. But in the control of prosthetic device using the EMG signal can be used the EMG signal with long transient or steady state types [9]. Therefore, in this study each movement will be maintained for the long time duration (long dynamic movement).

II. EXPERIMENTS AND DATA ACQUISITION

The EMG signals that were used in the evaluation were recorded from ten normal subjects with seven upper-limb movements and eight muscle positions. The seven upper-limb movements including wrist flexion (wf), wrist extension (we), hand close (hc), hand open (ho), forearm pronation (fp), and forearm supination (fs) are shown in Fig. 1 and the eight muscle positions are located on the right arm, as shown in Fig. 2. These data sets were acquired by the Carleton University in Canada [10]. A duo-trode Ag-AgCl surface electrode (Myotronics, 6140) was used and an

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Ag-AgCl Red-Dot surface electrode (3M, 2237) was placed on the wrist to provide a common ground reference. This system set a band-pass filter with a 1-1000 Hz bandwidth and amplifier with a 60 dB (Grass Telefactor, Model 15). The EMG signals were sampled by using an analog-to-digital converter board (National Instruments, PCI-6071E), and the sampling frequency was 3 kHz. However, in order to reduce the computational time and reduce the effect of noises, down sampling of the EMG data from 3 kHz to 1 kHz was done and bad-pass filter in range of 20 to 500 Hz was also implemented. Moreover, there are ninety-six data sets per movement for each subject and each data set contains the action EMG signal in 3-second duration.

III. METHODS

A. Feature Extraction Methods

In this study, we evaluate different kinds of features that have been widely used in EMG upper-limb prostheses control and there are up-to-date to the available techniques today [1-11]. Fifteen features from time domain and frequency domain are used in evaluation. Their mathematical definitions are presented in Table 1. All introduced features in time and frequency domains can be implemented in real-time application. Thirteen features in time domain including integrated EMG, mean absolute value, modified mean absolute value 1 and 2, mean absolute value slope, simple square integral, variance of EMG, root mean square, waveform length, zero crossing, slope sign change, Willison amplitude, and auto-regressive model. Moreover, two features based on frequency domain are mean frequency and median frequency. In addition, some specific parameters in feature methods are fixed i.e. the number of segments I of MAVS is 2, the order of AR model is 1, and the threshold parameter of ZC, SSC and WAMP is chosen between 10 and 100 mV.

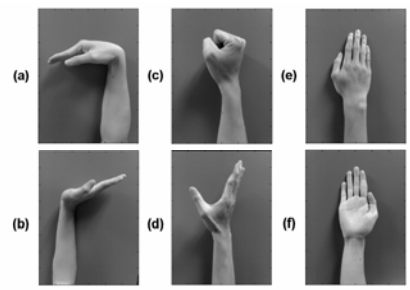

Fig. 1 Estimated six upper-limb movements (a) wf (b) we (c) hc (d) ho (e) fp (f) fs [11]

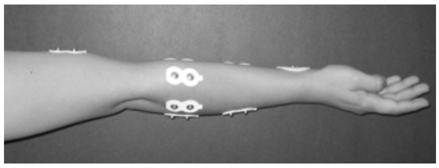

Fig. 2 The eight muscle positions on the right arm [11]

Table 1 Mathematical definition of the EMG feature extraction methods. Let x_n represents the EMG signal in a segment n. N denotes the length of the EMG signal. w_n is the continuous weighting window function. I is the number of segments covering EMG signal. a_i is the linear predictive coefficients. $\hat{x}_n$ is the predicted EMG signal value. P_j is the EMG power spectrum at frequency bin j. f_j is the frequency of the EMG power spectrum at frequency bin j

Feature extraction	Definition
Integrated EMG (IEMG)	$\text{IEMG} = \sum_{n=1}^{N} \lvert x_n \rvert$
Mean absolute value (MAV)	$\text{MAV} = \frac{1}{N}\sum_{n=1}^{N} \lvert x_n \rvert$
Modified Mean Absolute Value 1 (MAV1)	$\text{MAV1} = \frac{1}{N}\sum_{n=1}^{N} w_n \lvert x_n \rvert$, $w_n = \begin{cases} 1, & \textit{if } 0.25N \le n \le 0.75N \\ 0.5, & \text{otherwise} \end{cases}$
Modified Mean Absolute Value 2 (MAV2)	$\text{MAV2} = \frac{1}{N}\sum_{n=1}^{N} w_n \lvert x_n \rvert$, $w_n = \begin{cases} 1, & \textit{if } 0.25N \le n \le 0.75N \\ 4n/N, & \textit{if } 0.25N > n \\ 4(n-N)/N, & \textit{if } 0.75N < n. \end{cases}$
Mean Absolute Value Slope (MAVS)	$\text{MAVS}_i = \text{MAV}_{i+1} - \text{MAV}_i;\ i = 1, \ldots, I-1.$
Simple Square Integral (SSI)	$\text{SSI} = \sum_{n=1}^{N} \lvert x_n \rvert^2$
Variance of EMG (VAR)	$\text{VAR} = \frac{1}{N-1}\sum_{n=1}^{N} x_n^2$
Root Mean Square (RMS)	$\text{RMS} = \sqrt{\frac{1}{N}\sum_{n=1}^{N} x_n^2}$
Waveform length (WL)	$\text{WL} = \sum_{n=1}^{N-1} \lvert x_{n+1} - x_n \rvert$
Zero crossing (ZC)	$\text{ZC} = \sum_{n=1}^{N-1}\left[\operatorname{sgn}(x_n \times x_{n+1}) \cap \lvert x_n - x_{n+1} \rvert \ge \textit{threshold}\right]$; $\operatorname{sgn}(x) = \begin{cases} 1, & \textit{if } x \ge \textit{threshold} \\ 0, & \text{otherwise} \end{cases}$
Slope Sign Change (SSC)	$\text{SSC} = \sum_{n=2}^{N-1}\left[f\left[(x_n - x_{n-1}) \times (x_n - x_{n+1})\right]\right]$; $f(x) = \begin{cases} 1, & \textit{if } x \ge \textit{threshold} \\ 0, & \text{otherwise} \end{cases}$

Table 1 (*continued*)

Willison amplitude (WAMP)	$\mathrm{WAMP} = \sum_{n=1}^{N-1} f\left(\left\|x_n - x_{n+1}\right\|\right);$ $f(x) = \begin{cases} 1, & \textit{if } x \geq \textit{threshold} \\ 0, & \text{otherwise} \end{cases}$
Auto-regressive (AR) coefficients	$x_n = -\sum_{i=1}^{p} a_i x_{n-i} + w_n$
Median Frequency (MDF)	$\sum_{j=1}^{\mathrm{MDF}} P_j = \sum_{j=\mathrm{MDF}}^{M} P_j = \frac{1}{2}\sum_{j=1}^{M} P_j$
Mean Frequency (MNF)	$\mathrm{MNF} = \sum_{j=1}^{M} f_j P_j \Big/ \sum_{j=1}^{M} P_j$

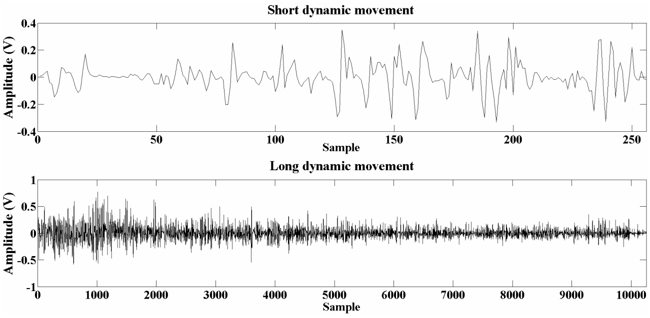

Fig. 3 The EMG signals recorded from wrist flexion movement with (up) short dynamic movement, 0.3 s in duration (down) long dynamic movement, 3 s in duration

B. Evaluation Criterion

The EMG signal in this study acquired from the long movement duration that we called “long dynamic movement”. It is difference to our previous study [8] that the movement was performed with a short duration. We can observe difference between short and long dynamic movements in Fig. 3. However, in order to reach the real-time system, the decision process should be finished with 1/3 s in duration that the window size should be less than 300 ms. In this study we have been proposed three window size function, i.e., 256, 128, and 64 ms. The disjoint segmentation was employed to get a series of feature from a long EMG data. However, we can notice that when the muscle contraction is maintained for a long period the amplitude of the EMG signal is dropped. This will be difficult to classify the correct movement. However, if the system can recognize a long time movement the utility of its control system will be increase.

In order to quantity the performance of the EMG features, class separability viewpoint is a main concern. A good quality in class separation means that the result of classification accuracy will be as high as possible. In other words, the maximum separation between classes is obtained and the small value of the variation in subject experiment is reached. In this study, we used the scatter graph and the RES index (statistical measurement method) as the evaluation criterions. The definition of the RES index [8] that used in this study is as follows. The EMG features in the matrix form can be expressed as

$$F_{i,j}^{k} = \begin{bmatrix} f_{1,1}^{k} & f_{1,2}^{k} & \cdots & f_{1,\mathrm{J}}^{k} \\ f_{2,1}^{k} & f_{2,2}^{k} & \cdots & f_{2,\mathrm{J}}^{k} \\ \vdots & \vdots & \ddots & \vdots \\ f_{\mathrm{I},1}^{k} & f_{\mathrm{I},2}^{k} & \cdots & f_{\mathrm{I},\mathrm{J}}^{k} \end{bmatrix}, \tag{1}$$

where f is the EMG feature, i is the channel number ($1 \leq i \leq$ I, I = 8), j is the window number ($1 \leq j \leq$ J, J = floor(L/N)), N is length of the window size function, L is the whole data set length of each EMG motion ($L \approx 3072$) and k is the motion number ($1 \leq k \leq$ K, K = 6). Note that the EMG feature values from each channel of all motions were normalized to be in the range of 0 and 1 which can be expressed as

$$f_{norm} = \frac{f - \min(f)}{\max(f) - \min(f)}. \tag{2}$$

The average of the EMG feature values of each channel can be given by

$$\overline{\mathrm{F}}_{i}^{k} = \begin{bmatrix} \overline{f}_{1}^{k} \\ \vdots \\ \overline{f}_{i}^{k} \end{bmatrix}, \tag{3}$$

where $\overline{f}_{i}^{k}$ is calculated from the definition in Table 1.

The standard deviation of the EMG feature values of each channel can be defined as

$$\mathrm{S}_{i}^{k} = \begin{bmatrix} s_{1}^{k} \\ \vdots \\ s_{i}^{k} \end{bmatrix}, \tag{4}$$

where

$$s_{i}^{k} = \sqrt{\frac{\sum_{j=1}^{\mathrm{J}} (f_{i,j}^{k} - \overline{f}_{i}^{k})^2}{\mathrm{J}}}, \tag{5}$$

The mathematical definition of the RES index can be expressed as

$$\text{RES index} = \frac{\overline{ED}}{\overline{\sigma}}, \tag{6}$$

where

$$\overline{ED} = \frac{2}{\mathrm{K(K\text{-}1)}} \sum_{p=1}^{\mathrm{K}\text{-}1} \sum_{q=p+1}^{\mathrm{K}} \sqrt{(\overline{f}_1^{\,p} - \overline{f}_1^{\,q})^2 + \ldots + (\overline{f}_{\mathrm{I}}^{\,p} - \overline{f}_{\mathrm{I}}^{\,q})^2} \quad , (7)$$

$$\overline{\sigma} = \frac{1}{\mathrm{IK}} \sum_{i=1}^{\mathrm{I}} \sum_{k=1}^{\mathrm{K}} s_i^k \ , \qquad (8)$$

and p and q are motion number (1=wf, 2=we, 3=hc, 4=ho, 5=fp, and 6=fs). The performance will be best when the RES index obtain the high value. Moreover, this index is proved in the previous work that it exhibited the same trend with the efficient classifiers.

IV. RESULTS AND DISCUSSION

To demonstrate the performance of classification, in this paper, we used the RES index to indicate the quality of class separation instead of using only the observation from scatter plot. From the experimental results, the WAMP is the best feature compared to the other EMG features as we can observe from the Figs. 4(a) to 4(c). The WAMP with 0.025 V threshold obtains the RES index in range of 3.8-7.2. Its average value is approximately 5.1-5.3. Its RES index is higher than the RES index of the secondary feature group about 1.0. The WL, RMS, MAV, IEMG, and MAV1 are the secondary features group. Their RES indexes are greater than 4.0 at the 128-ms and 64-ms window size functions. Moreover, they provide only one feature per channel which is small enough to combine with the other features to make a more powerful feature vector while it does not increase the computational burden for the classifier. The ZC with 0.005 V threshold, MAV2, VAR, and SSI are closed by the secondary features group. Their RES indexes are approx. 3.5. The other features obtain the poor RES indexes that are not recommend to use in a feature vector.

However, in order to reduce the EMG features to the smallest dimension feature vector, we can remove features that have the same pattern that we can observe that from the scatter plots. In more details, in case of time domain features that are calculated based on their amplitudes, we found that features in the secondary group have the same pattern. Thus only the best one in this group is recommended that is the WL feature with 128-ms window size function. In addition, for the time domain features that obtained the frequency information, WAMP has the better in cluster separability than ZC and SSC. The optimal threshold value of WAMP is about 25 mV and the optimal threshold value of ZC and SSC is 5 and 2 mV, respectively. Furthermore, the modified version of the MAV is worse than its traditional version. The whole features in frequency domain show poor class separability. The MDF obtains the larger RES index than the MNF. Nevertheless, the MAVS is the worst classifier performance compared to the other features. Its maximum RES index is only 1.5. Additionally, the AR and MAVS in this study used the first order and two segments for obtaining only one feature per channel. Therefore, the increasing of the AR order and the MAVS segment may improve the classification results in the future test.

The effect of the window size function is found that there is not the same trend in each feature. The VAR, SSI, SSC, MDF, and MNF features obtain the higher RES index when the window size function is set to 256 ms. While the window size function is set to 128 ms, the WAMP, WL, RMS, MAV1, MAV2, and ZC get the higher RES index value. In addition, the MAV, IEMG, AR, and MAVS acquire the high RES index value when 64-ms window size function is set.

From the experimental results and discussions above we can recommend that the WAMP with threshold 0.025 V and WL will be made an efficient feature vector. It should provide the high classification accuracy. Moreover, the suggestion of the EMG features in this study is same as the recommend feature in our previous study [8]. The order of the best feature is difference but the better feature group is the same one. Thus the use of the EMG signal with the short or long dynamic contractions is not affected to the evaluation of the feature methods. In the future work, the other features that have been reported in the literatures should be evaluated to find the better one. Moreover, the combination of some useful features should be tested using the achievement classifiers to find optimal feature vector for the EMG recognition system.

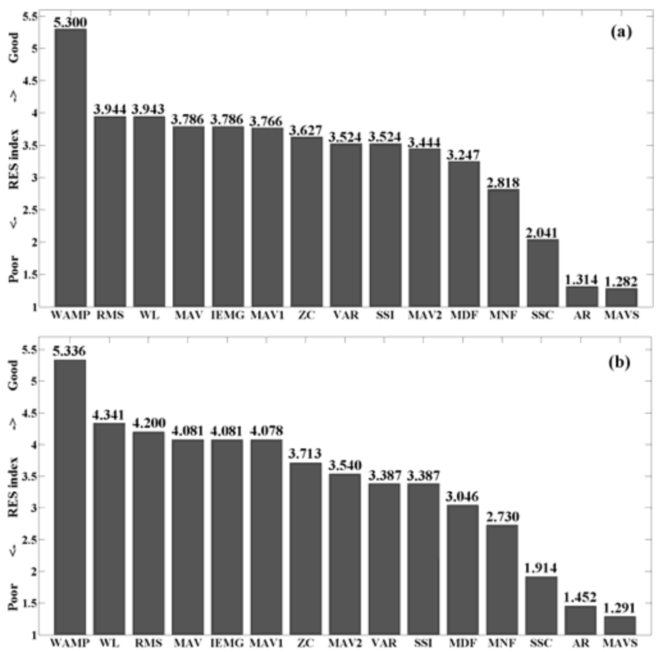

Fig. 4 Bar plot of the average RES index of fifteen EMG features with the six different movements and eight muscles of ten subjects at window size (a) 256 ms (b) 128 ms (c) 64 ms

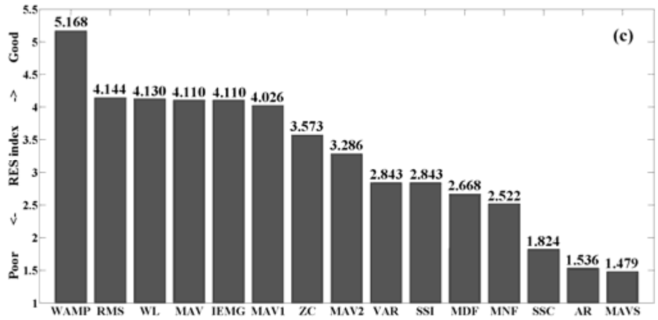

Fig. 4(*continued*)

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