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A Modified Multi-Channel EMG Feature for Upper Limb Motion Pattern Recognition

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***Abstract*— The EMG signal is a well-known and useful biomedical signal. Much information related to muscles and human motions is included in EMG signals. Many approaches have proposed various methods that tried to recognize human motion via EMG signals. However, one of the critical problems of motion pattern recognition is that the performance of recognition is easily affected by the normalization procedure and may not work well on different days. In this paper, a modified feature of the multi-channel EMG signal is proposed and the normalization procedure is also simplified by using this modified feature. To recognize motion pattern, we applied the support vector machine (SVM) to build the motion pattern recognition model. In training and validation procedures, we used the 2-DoF exoskeleton robot arm system to do the designed pose, and the multi-channel EMG signals were obtained while the user resisted the robot. Experiment results indicate that the performance of applying the proposed feature (94.9%) is better than that of conventional features. Moreover, the performances of the recognition model, which applies the modified feature to recognize the motions on different days, are more stable than other conventional features.**

I. INTRODUCTION

The EMG signal is the electrical potential generated by muscle cells when these cells are mechanically active. It has been applied to many areas, such as medical research, rehabilitation, ergonomics and sports science. It has also been used by engineers to control robots. A wearable exoskeleton robot system is more useful to assist humans, especially for the disabled. Generally, there are two studies for control robots based on using EMG signals. One of the two studies focuses on building a muscle-skeleton model via EMG signals to control robots. The other study on controlling robots focuses on applying the machine-learning method to recognize the motion.

There have been many approaches to build a muscle-skeleton model. Rosen *et al.* [1] presented a method to control a powered exoskeleton. They used the Hill-based muscle skeleton model and the EMG signals to model the human arm status. Fleischer *et al.* [2] proposed the dynamic human body model (DHBM) and the direct force control (DFC) to achieve exoskeleton control. By using the muscle model, the force produced by the muscle can also be approximated. However, the muscle internal information such as muscle fiber length has to be given before building the muscle model. For this reason, the other way of applying machine-learning methods was proposed. In this method, determining how to extract features from EMG signals and a suitable machine learning method are the important issues. Over the past decades, a lot of research focused on feature extraction and machine learning methods. In 1993, Hudgins *et al.* [3] proposed five kinds of time-domain (TD) features, and applied artificial neural networks to recognize upper limb motions. The TD features are mean absolute value (MAV), mean absolute value slope, zero crossing (ZC), slope sign changes (SSC) and waveform length (WL). Fukuda *et al.* used the EMG signals to teleoperate a human-assisting manipulator. They estimated the mean absolute value of the EMG signals and applied a novel statistical neural network for EMG pattern discrimination. The network was trained to recognize the human arm posture by the EMG pattern and the 3-D position sensor [4]. In 2004, Fukuda *et al.* [5] proposed a control method to control a wearable robot arm. The neuro-fuzzy network was employed.

Frequency-domain features as well as TD features have been applied. Englehart *et al.* [6] showed the result of motion recognition by using frequency-domain (FD) features. The common FD features are the coefficients of short-time Fourier transform (STFT), the coefficients of wavelet transform (WT), and the coefficients of auto-regression (AR) of the spectrum of EMG signals. The auto-regression feature was applied to the application of muscle fatigue in 1987. Since then, many research groups have been trying to use this feature in motion recognition. When many kinds of feature extraction methods were proposed, the various combining methods were also employed. Englehart *et al.* [7] tried to use TD and FD features to recognize the wrist and palm motions. In this approach, FD features including STFT and WT were combined with the conventional TD features to build the recognition model. In 2005, Chan *et al.* [8] used the AR features and the Gaussian mixture model (GMM) to extract the FD feature of EMG and classify the forearm motion. With the same machine learning method, Huang *et al.* [9] also applied the GMM method to recognize the motion for controlling the upper-limb prostheses. They compared with the performances of three kinds of combining features, which used TD, AR + RMS, AR + RMS + TD. Moreover, Oskoei *et al.* [10] made similar comparisons. They applied SVM, which is widely used in the machine learning method, and tried various combined features. These methods included only TD, FD features, and the combination of TD and FD features.

Although numerous studies have proposed many kinds of features and recognition methods, recognizing motions generated at different times or days was not discussed. For this reason, some experiments pertaining to motion pattern

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recognition on different days in this paper have been designed to compare the performances. The modified feature is also proposed to simplify the normalization procedure and to provide better performance than conventional features in our experiments. The rest of this paper is organized as follows. Section II introduces the exoskeleton robot arm system and data acquisition system, which was used to help the user produce the designed actions. Section III presents the entire motion pattern recognition procedure, including muscle onset time detection, with the modified feature. Then, the design of our experiment results will be shown and discussed. Finally, section V summarizes the conclusions.

II. Data Collection and Robot System

For the motion pattern recognition based on multi-channel EMG signals, six-channel EMG signals were collected. In this paper, the motions of shoulder and elbow joints in the saggital plane were defined as the shoulder flexion/extension and elbow flexion/extension. For the elbow flexion/extension, the biceps brachii and triceps brachii were selected. For the shoulder motions, anterior deltoid, posterior deltoid, pectroalis major and teres major were applied. To measure the EMG signals, surface EMG electrodes (Ag/AgCl) were employed. To avoid the factor resulting from the different distances between the electrodes, the pair of electrodes was placed close to keep the distance fixed. The fixed distance was about double the radius of a single electrode since the electrodes were closed. These six-channel EMG signals were sampled at 1 kHz using a 12-bit data acquisition card made by National Instruments.

To obtain the multi-channel EMG signals of the designed pose, an exoskeleton robot arm system was used to help the user to generate the EMG signals. In this robot system, there are two degrees of freedom that correspond to the shoulder and elbow joints of the human body. In the training procedure, a set of poses was designed and used to control the robot arm. While the robot was executing the poses, the user was required to resist the robot arm. While the user was resisting, the recorded multi-channel EMG signals represented the pose opposite the robot motion. For example, the multi-channel EMG signals were generated by elbow extension when the robot arm was lifting up. Then, the set of multi-channel EMG signals was labeled as elbow extension in the training procedure and in the validation procedure. Additional details of the training and validation procedure are discussed in the experiments.

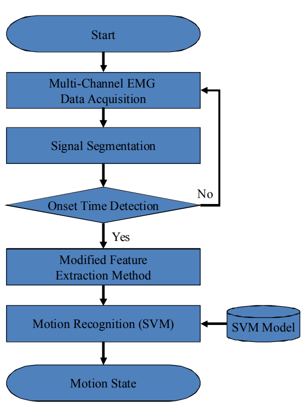


Figure 1. Flow chart of motion pattern recognition

III. The Method of Upper Limb Motion Classification

The entire processing of upper limb motion classification is presented in Fig. 1. When the multi-channel EMG signals are obtained, the front-end signal processing, including segmentation and onset time detection, will be executed. Then the features are extracted for building the motion classification model or recognizing the motion.

A. Muscle Onset Detection Method

In the front-end signal processing, segmentation is the first step. For the EMG signals in each channel, they are segmented per 256 samples, and the features will be extracted and used to recognize the motion of this segment. In addition to feature extraction and motion pattern recognition, muscle onset time detection is the other critical component to determine whether the muscle is active in this segment. In the conventional method, the standard deviation of the baseline part is estimated in the raw EMG signal or the RMS of the EMG. Then several times the standard deviation is set as the threshold to define the muscle activity. In this paper, the other onset time detection method is applied. The Teager-Kaiser energy (TKE) operator [11] is widely used in speech and communication approaches such as AM and FM modulation. Recently, the TKE operator was employed to detect the EMG onset time. The equation of the TKE operator is denoted as (1). The signal $x(n)$ is assumed as a cosine signal where A, $\omega(n)$ and θ are amplitude, angular frequency and phase in (2). When $x(n)$ is processed by the TKE operator, the approximated result is derived in (3).

$$\Psi[x(n)] = x^2(n) - x(n+1)x(n-1) \tag{1}$$

$$x(n) = A \cdot \cos(w(n) + \theta) \tag{2}$$

$$\Psi[x(n)] \cong A^2 \cdot \sin^2(w(n)) \tag{3}$$

Equation (3) shows the advantage of the TKE operator, namely that the frequency and amplitude of $x(n)$ are enhanced without mapping to the frequency-domain; this is the main reason that we apply this operator. The EMG signals in each channel are calculated by (1) and three times the standard deviation value of baseline signals is set as the threshold to determine whether the muscle is active in that segment.

B. The Features of EMG Signals

When the active segment is detected, the features of this segment are extracted. The features include TD and FD types. In this paper, the performances of different methods that combine TD and FD features are compared. The conventional TD features are MAV, ZC, SSC, WL [3] and RMS [8]. The threshold used to detect the onset time is applied to be *TH* in the equations of ZC and SSC. The *TH* is used to avoid the baseline noise being counted. Frequency-domain features are the other types of features; they are the coefficients of STFT, the coefficients of AR, median frequency of power spectrum (MPF) and mean power frequency (MF) [12]. In the frequency-domain, the 1st to 250th coefficients of STFT are used to be the features. The sixth order of AR is usually applied, as in this paper.

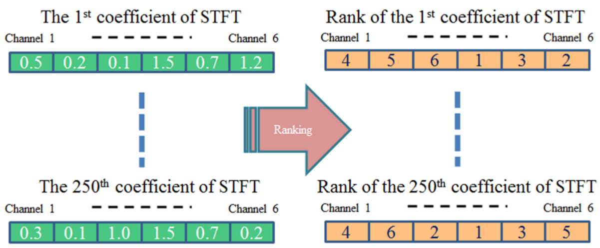


Figure 2. Main concept of the Rank feature

In some papers, the use of combined TD and FD features in a feature vector is usually employed. However, the normalization procedure has to be executed since the magnitudes of the features or signals are different in different experiments no matter whether the user or the motion is the same. Nevertheless, the relationship between muscles in the same user and motion is similar. For this reason, the novel feature is proposed herein. The feature, the modification of the coefficients of STFT, is called Rank of STFT. The main concept of the Rank of STFT method is depicted as Fig. 2. For the goal of the motion pattern recognition, the six kinds of muscles are applied. Therefore, the coefficients of STFT in each muscle are ranked from 1 to 6. To calculate the Rank of STFT, the 1st to 250th coefficients of STFT in each muscle are separated into several bins. The bin is denoted as (4). The $Bin_{b,m}$ means the b^{th} bin of the m^{th} muscle. The parameter N represents the number of frequency elements in each bin.

$$Bin_{b,\,m}=\frac{1}{N}\sum_{k=1}^{N} f_m(N\cdot b+k)\,,\; b=0,1,2,\ldots,\frac{250}{N}-1 \qquad (4)$$

The dimensions of the Rank of STFT are able to be reduced after using the bin method. For example, the dimensions of ranking 25 bins in six-channel EMG signals are 150. Through the ranking process, the feature is meaningful and represents the relationship between muscles; it does not just combine the features into a vector.

Moreover, the normalization procedure is also simplified based on the ranking method. In the typical motion pattern recognition, the maximum and minimum value of each feature should be estimated to normalize features. In contrast with the typical method, the maximum and minimum values, which are the number of applied muscles and 1, have been known since the rank processing. Given this advantage, the normalization procedure can be simplified, and make the performance of motion pattern recognition is better than using conventional features in different experiments.

C. *Classification Method*

The SVM method is a commonly used machine-learning method. There are several kernel functions in SVM, such as: linear, RBF (radial basis function), polynomial and sigmoid functions. The data are mapped to high dimensional space through the use of the kernel functions. Then the mapped data are expected to be easily separated in the high dimensional space by using the hyper plane. The best hyper plane is defined by maximizing the margin between the boundaries. The boundaries are made by the data in each class. In our experiments, the RBF is applied to build recognition models. The performances based on using conventional methods and the proposed features are compared in the same kernel function.

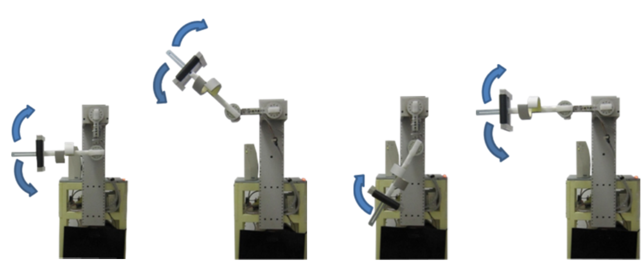
IV. EXPERIMENTS

To verify the proposed method, the multi-channel EMG signals were obtained from a thirty-year-old healthy male subject. There are seven trials in our experiments. Each trial, including training and validation procedures, was executed every two days in two weeks, in order to avoid muscle fatigue. The motion scenario was designed for the training procedure. When the robot arm was moving to achieve the poses of the scenario, the subject was required to resist the robot arm. Therefore, the generated EMG signals of the motions opposite to the robot arm would be measured and labeled. The rotation angles of the shoulder and elbow are zero when the forearm and upper arm are perpendicular to the ground. The rotation angle is positive when the movement of shoulder or elbow is flexion. According to the coordination definition, the motion scenario is described in Table I. There are six motions in the scenario, and the user is able to rest for 10 sec between each motion. In contrast with the training procedure, the robot arm is static in the validation procedure when the user resisted the arm. The poses for validation are shown in Fig. 3. In Fig. 3 (b) and (c), the angles of the elbow are 45° and 15° , respectively.

In this paper, the performances of seven combined features are compared. The seven features are TD (MAV + ZC + SSC + WL), AR + RMS, AR + RMS + TD, MAV, AR + STFT + MPF + MF, STFT, and the proposed feature (Rank of STFT). Those seven features are denoted as f_1 to f_7 in the following comparisons. As already mentioned, there are seven trials in two weeks. Each trial includes training and the validation procedure. The features of the multi-channel EMG signals were normalized by the maximum and minimum of the features from the data in the training procedures of each trial. Because the values are known previously, using the Rank of STFT does not require calculating the maximum and minimum values. This is why the proposed feature is able to simplify the normalization procedure.

TABLE I. THE DESIGNED POSES FOR TRAINING PROCEDURE

Motion	Shoulder	Elbow
#1	Lifting up from 0° ~ 90°	Fixed
#2	Fixed	Lifting up from 0° ~ 90°
#3	Fixed	Lying down from 90° ~ 0°
#4	Lying down from 90° ~ 0°	Fixed
#5	Fixed	Lifting up from 0° ~ 90°
#6	Fixed	Lying down from 90° ~ 0°



(a) (b) (c) (d)

Figure 3. The poses for validation procedure.
(a) Shoulder lifting up/lying down (b) Elbow lifting up/lying down
(c) Elbow lifting up (d) Shoulder lifting up/lying down

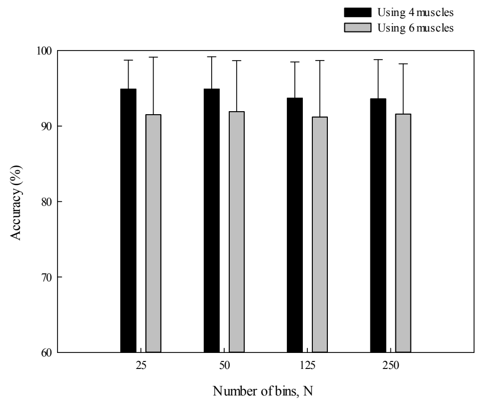


Figure 4. Comparison of the average performances achieved using different features in seven trials

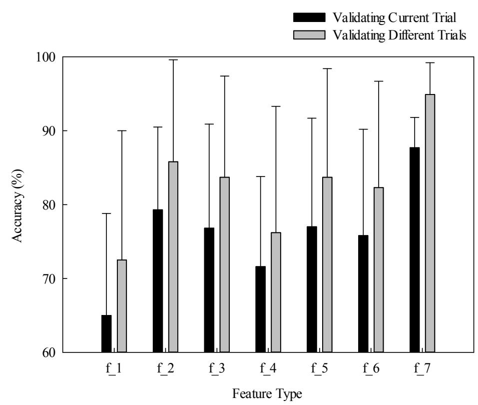


Figure 5. Comparison of the average performances of using different features to validate current and different trials

In our experiments, the performances of four separation methods, 25, 50, 125 and 250 bins, are compared. Fig. 4 illustrates that using 50 bins (94.9%) produces a better result than using any other number. Moreover, the result also indicates that using four muscles (biceps, triceps, anterior deltoid and posterior deltoid) is better than using six muscles. The comparison shows the pectroalis major and teres major may not provide the key contributions for generating the designed poses. The advantage of using four muscles is that the dimensions of the feature vector will be reduced. In Fig. 5, the black bars show the average performances achieved using the seven features to validate the poses in seven trials. In cross-trial validation, one of seven models trained by the training data of the current trail is used to validate the validation data of the rest six trails. Obviously, using Rank of STFT (94.9%) is better than using other features. The comparison with the standard deviations also indicates the performance of using Rank of STFT is more stable than using conventional features. The gray bars in this figure show the other important results. In the approaches of motion pattern recognition based on EMG signals, the performance based on using the recognition model will become worse when validating the motions on different days or at different times. The factors making the performance worse are various such as skin impedance, the position of EMG surface electrodes, and so on. In this paper, our assumption is that the normalization procedure might be one of the interference factors. The maximum and minimum values of EMG signals and features might be different on different days. However, the behaviors of the EMG signals in the same motion should be similar. Using Rank of STFT facilitates maintaining the behavior between muscles. The gray bars in Fig. 5 show the average accuracy produced by using one of the seven models to validate the motions of the other six trials. The result shows the performance of Rank of STFT (*f_7,* 87.7%) is better and more stable than the performances using other features.

V. Conclusions

A novel feature, Rank of STFT, is proposed by modifying the conventional features. The experimental results show that the accuracy of using the Rank of STFT is 94.9% which is better and more stable than that achieved using traditional features. Moreover, the normalization procedure is simplified since the maximum and minimum values were previously known. To validate the motions on different days or at different times, the accuracy of the Rank of STFT is 87.7%, which also has better performance than that achieved by using the other features.

The use of the Rank of STFT feature not only facilitates maintaining the behavior of muscles but also achieves a better performance. In the future, the comparison of applying this approach with different subjects will be studied, and the method will be used in controlling exoskeleton robot arms.

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