Wrist Motion Recognition by Using Electromyographic Signals

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***Abstract*—Wrist motion classification is a very common research topic in scientific study. However, wrist motion recognition of the surgeon is often neglected in the robot-assisted surgery or surgical training. Therefore, the objective is to develop a classification method to recognize wrist motion of the surgeon. In order to do that, we present a linear discriminant analysis (LDA) algorithm involving surface electromyography (sEMG) signals to evaluate the motions in this paper. Firstly, sEMG signals are collected by using a MYO armband which can be worn on the forearm of a subject. Root-mean-square (RMS) and waveform length (WL) feature are extracted from the sEMG signals and then those features are regarded as input of the LDA to train the classifier. As a result, we can obtain a classifier to recognize four kinds of wrist motions. Classification experiment is performed by two subjects. The experimental results have been demonstrated by using the proposed approach and it is shown that the accuracy of wrist motion by using RMS feature is higher than that of by using WL feature.**

I. Introduction

Recently, motion capture technology (MCT) is very widely used in many areas involving 3D digital animation, sports and exercise research, medical applications, and neuroscience research, etc. [1] [2] [3] [4]. The motion capture covers position tracking of human, feature extraction, pattern and recognition [5].

In order to recognize motion pattern, kinematic information, such as position, angle, velocity, can be used as input of MCT. At the same time, physiological signal also can be applied to evaluate the motion pattern of human [6] [7] [8]. In general, it cannot acquire neural information of human motion pattern according to the physical information. However, the physiological signals, such as surface electromyogram (sEMG), electroencephalogram(EEG), and electrooculogram (EOG), can help human to analyse neural pattern of motion [9] [10]. The sEMG signals indicate the effect of human's motor unit action potentials of the muscle fiber. Motion intention pattern of the human can be evaluated by using sEMG signals [11] [12].

Many achievements indicated that feature of the sEMG signals could further improve the recognition accuracy of the motion pattern [13] [14] [15]. According to [16], Atoufi *et al.* used mean absolute values (MAV) of the sEMG signals as the feature to evaluate the muscle synergy. Yang *et al.* used variety of EMG signal variations to recognize multiple finger motions [17]. In [18], a five time series features was presented to compare the performance of motion pattern by using MYO armband. A common spatial pattern (CSP) feature showed a better performance in comparison with time domain (TD) features for classification accuracy [19]. In [20], Akhlaghi *et al.* used ultrasound imaging of human arm to recognize the complex volitional hand motion in real time. Bhattacharya *et al.* proposed a hybrid multi-feature method to control limb prosthses for human computer interfaces [21]. A top and slope (TAS) feature of sEMG signals were introduced to detect lower limb human motion and it could provid high accuracy in the experiments [22]. According to [23], Daubechies wavelet transform method was presented to evaluate the performance of the feature extraction.

To improve the recognition accuracy of the motion pattern, many researchers have concentrated on how to analyse the motion intention [24] [25]. Chambon [26] *et al.* proposed a deep learning architecture with multivariate and multimodal time series for sleep stage classification. In [27], a hybrid algorithm involving Bayesian and neural networks method was developed to motion classification for human-robot interfaces. A fuzzy logic algorithm was presented for wrist movements classification [28]. Ahsan *et al.* used an optimized neural network to evaluate EMG motion pattern [29]. In [30], a special subject-independent based decoding model was proposed to decode the wrist motions and hand motions.

Inspired by the feature extraction method and motion classification algorithms, a LDA method with different features was developed to recognize the wrist motions of the surgeon. In this work, we used WL and RMS feature as the input of classification model. In the process of experiment, we founded that the RMS feature can be achieved a higher accuracy in comparison with that of the WL feature. The feasibility of the proposed wrist motion recognition method was demonstrated by the experimental results.

The rest paper's structure is as below. The proposed method of data acquisition, feature extraction and classification are presented in Section II. Section III presents the experimental results which introduce the experimental setup and wrist motion classification experiment. Section IV contains the conclusion and the suggestions for future

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research.

II. PROPOSED METHOD

We propose a wrist motion framework as shown in Fig. 1 in this paper. It can be seen that this framework contains sEMG signals preprocessing, feature extraction, and classifier.

As shown in Figs. 2(a)-(d), four types of wrist motions are studied[1]. In the experiment, the subject is requested to do the wrist motion with maximal angle.

A. Data acquisition and feature extraction

As shown in Fig. 1, MYO armband (Thalmic Labs Inc.) is mainly utilized for acquisition of sEMG signals and it wears on the forearm of the subject[2]. The collected sEMG signal is showed in Fig. 3.

Root-mean-square (RMS) and waveform length (WL) are utilized to describe the features of the collected sEMG signals.

RMS feature of the sEMG signals is defined as below:

$$F_{RMS} = \sqrt{\frac{1}{W_{rms}} \sum_{i=1}^{W_{rms}} n_i^2}. \tag{1}$$

where W_{rms} represents the length of sampling moving window for RMS. n_i represents the collected sEMG signals. F_{RMS} represents the feature of sEMG signals for RMS. Fig. 4 shows the RMS feature.

WL feature of the sEMG signals is defined as below:

$$F_{WL} = \frac{1}{W_{wl}} \sum_{i=1}^{W_{wl}} \Delta n_i. \tag{2}$$

with

$$\Delta n_i = n_i - n_{i-1} \tag{3}$$

where W_{wl} represents the length of sampling moving window for WL. n_i represents the collected sEMG signals. F_{WL} represents the feature of sEMG signals for WL. The WL feature is presented in Fig. 5.

B. Training and classification

In the training and classification phase, we present a linear discriminant analysis (LDA) to train the classifier to recognize the wrist motion based on RMS feature and WL feature. In the experiment, the subjects train each wrist motion with two minutes, and then repeat 3 times.

In this work, K_i is the recognition result of the wrist motion. F is the feature of the collected sEMG signals[3]. According to the features, we can recognize the wrist motion type.

Based on [31] [32], the wrist motion result K_i can be defined as below:

$$p(K_i|F) = \frac{p(K_i)p(F|K_i)}{p(F)} \tag{4}$$

where $p(K_i)$ represents the prior probability of the wrist motion. $p(K_i|F)$ represents the posterior probability of the wrist motion by using the sEMG signal's features F. When the value of posterior probability is maximum for a certain wrist motion, we can be sure the recognition result by using the LDA method.

In general, $p(F|K_i)$ represents the contingent probability of the wrist motion, and it can be defined as below[4]:

$$p(F|K_i) = \frac{1}{\sqrt{(2\pi)^M det(D)}} \exp\{-\frac{1}{2}(F-\mu_i)^T D^{-1}(F-\mu_i)\} \tag{5}$$

where M represents the number of sEMG signal's feature vector. μ_i represents the mean vector of the wrist motion result K_i. D represent the covariance matrix for four types of wrist motions.

Logarithm fetch on Eq. 5, we can obtain the maximum value of the $p(K_i|F)$. And then the linear discriminant function (LDF) is defined as below:

$$\delta(k) = F^T \mu_g + c_g \tag{6}$$

with

$$\mu_g = D^{-1}\mu_k \tag{7}$$

$$c_g = -\frac{1}{2}\mu_k^T D^{-1}\mu_k \tag{8}$$

We maximize the LDF $\delta(k)$, the recognition result can be obtained according to the feature vector.

III. EXPERIMENTS AND RESULTS

In this section, an experiment is performed to recognize the four kinds of wrist motions (WR, WL, WE, and WF).

The process of this experiment can be presented as in Fig. 6.

A. Experimental setup

The experimental setup is conducted to evaluate the effectiveness of the wrist motion recognition method.

- *Hardware configuration*. Hardware configuration contains the MYO armband with 8 sensor (200 Hz), a work station with i7-3770T CPU (2.50GHz) and 12 GB internal storage.
- *Software configuration*. Software configuration includes MATLAB R2016a, VS 2013, and Windows seven operation system.

[1]The four wrist motion can be described as: wrist to the right (WtR), wrist to the left (WtL), wrist extension (WE), and wrist flexion (WF).

[2]The MYO armband collects the raw sEMG signals by using eight detection electrodes and a nine-axis inertial measurement unit with two hundreds sampling Hertz.

[3]In this paper, the features of the collected sEMG signals contain F_{RMS} and F_{WL}.

[4]In this paper, $p(f_{RMS}|c_k)$ can satisfy the multivariate probability distribution (MPD).

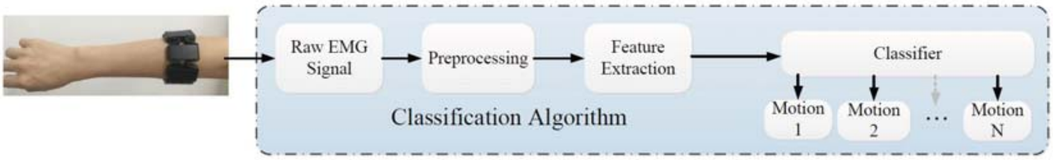

Fig. 1. The wrist motion framework.

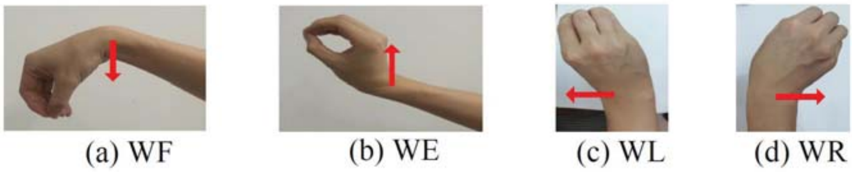

Fig. 2. Four kinds of wrist motions and the placement of the MYO armband on a right forearm.

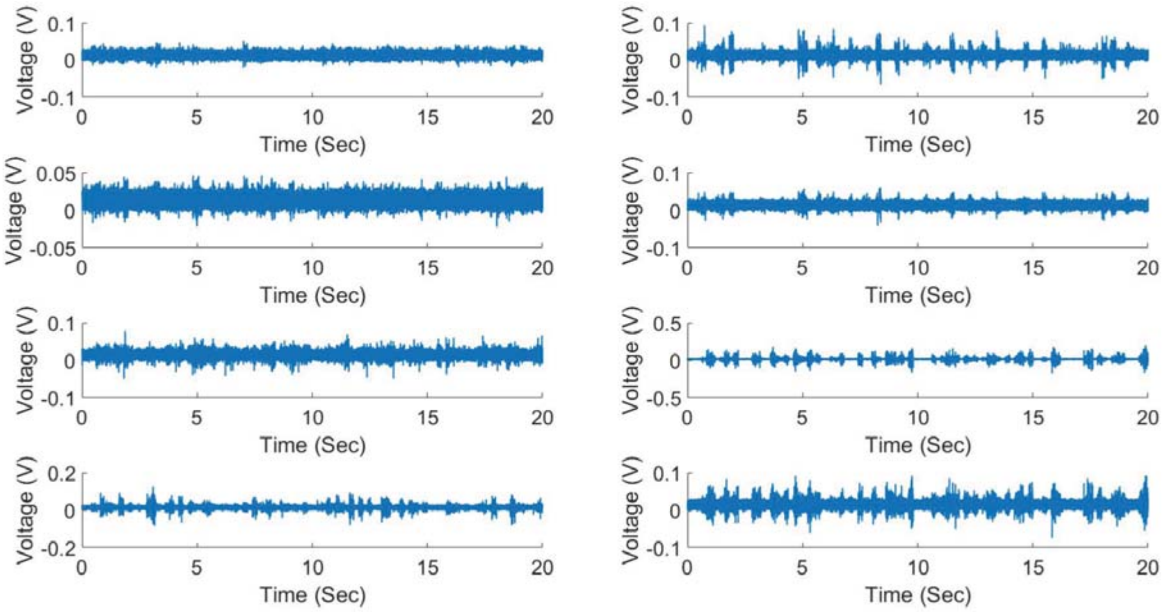

Fig. 3. The collected sEMG signals by using a MYO armband.

Accuracy (ACC) is used to evaluate the feasibility of the proposed method.

In this experiment, two healthy subjects (age 22-30 years old, 2 males) are invited to perform the four types or wrist motion with maximal angle. To minimize the influence of muscle fatigue for the subject, we request each subject perform two times with two minutes for each wrist motion, and then have a rest with thirty minutes. In order to discuss the impact of the difference features, we utilize the F_{RMS} and F_{WL} to represent the sEMG signal's feature. In the pilot experiment, the moving window size of F_{RMS} and F_{WL} are set as $W_{rms} = W_{wl} = 50$. We perform two experiments in this work. The experimental parameters of the two experiments can be presented as:

TABLE I
THE EXPERIMENTAL PARAMETERS OF THE TWO EXPERIMENTS

Experiment	Experiment 1	Experiment 2
Size of training set	250*8	20000*8
Size of testing set	200*8	20000*8
Feature	F_{RMS}, F_{WL}	F_{RMS}, F_{WL}
Size of moving window	50	50

B. Wrist motion classification experiment

In experiment 1, the classification results are presented in Tables II-III and Fig. 7. In Table II, WtL and WtR can be obtained the best performance of classification in comparison with that of other two wrist motions based on RMS feature. While, in Table III, the performance of classification of WtL

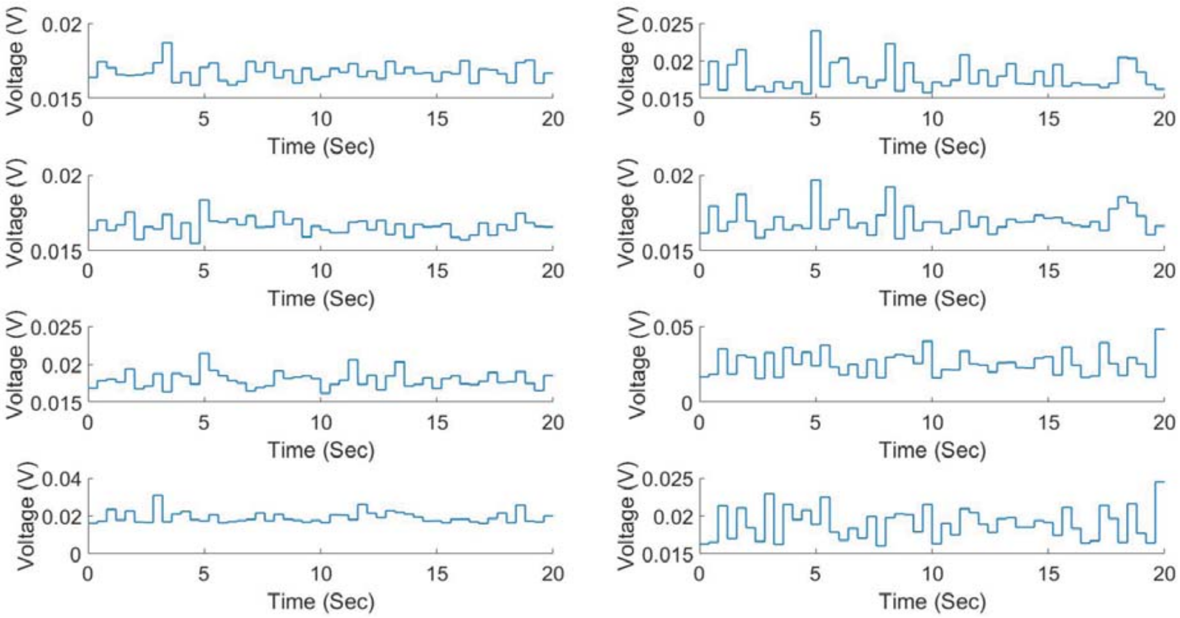

Fig. 4. The feature of sEMG by using RMS.

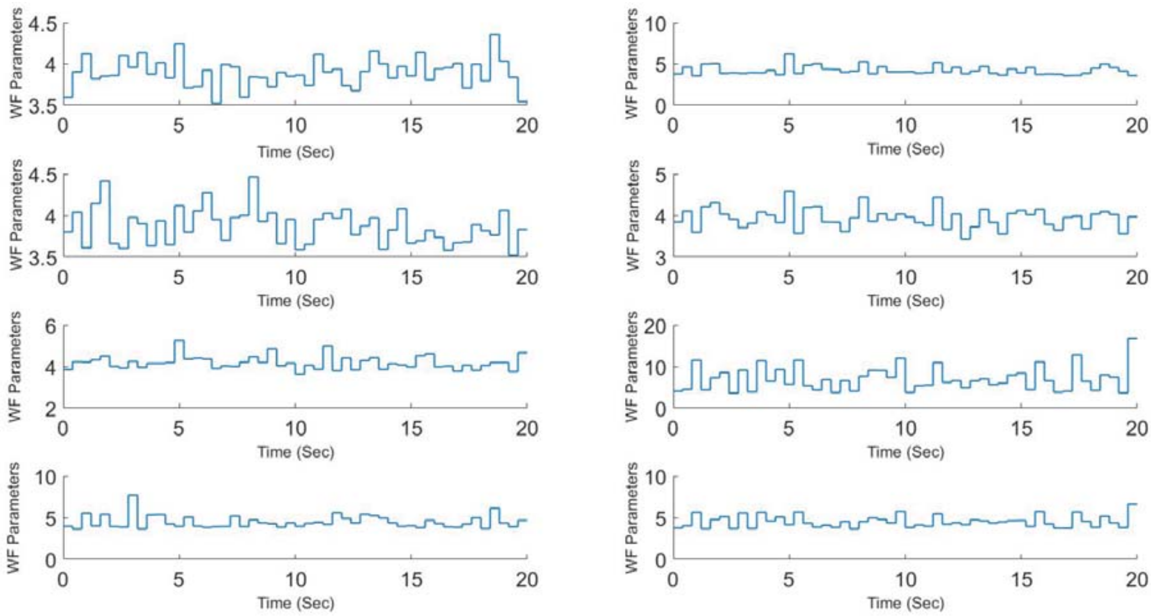

Fig. 5. The feature of sEMG by using WL.

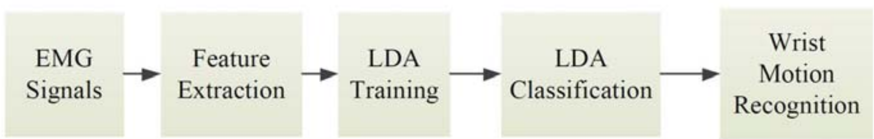

Fig. 6. Experiment process of the proposed wrist gesture classification and wrist stiffness estimation.

is best among four types of wrist motions. It can be concluded that the signal strength is different for wrist motions (WtL, WtR,WE and WF) for the same subject. In addition, sEMG signal for WtL and WtR is relatively strong in experiment 1.

The average classification accuracy by using the RMS feature is higher than that by using the WL feature from Fig. 7.

TABLE II
THE RESULTS OF WRIST GESTURE CLASSIFICATION FOR EXPERIMENT 1 BY USING RMS FEATURE.

Gesture	WtL	WtR	WE	WF
WtL	1	0	0	0
WtR	0	1	0	0
WE	0	0	0.8	0
WF	0	0	0	0.7

TABLE III
THE RESULTS OF WRIST GESTURE CLASSIFICATION FOR EXPERIMENT 1 BY USING WL FEATURE.

Gesture	WtL	WtR	WE	WF
WtL	1	0	0	0
WtR	0	0.7	0	0
WE	0	0	0.8	0
WF	0	0	0	0.8

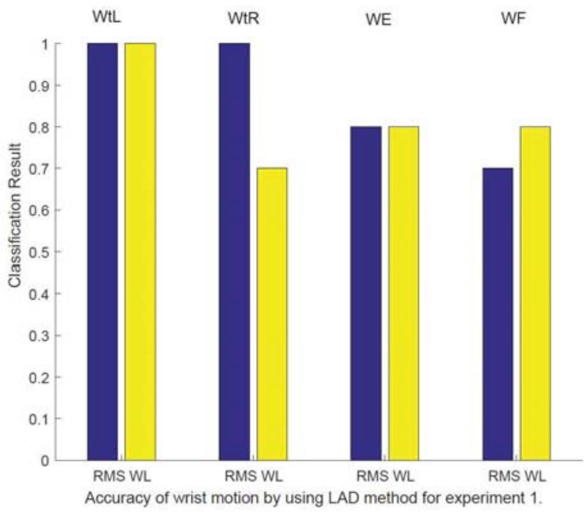

Fig. 7. Accuracy of wrist motion by using LAD method for experiment 1.

In experiment 2, Tables IV-V and Fig. 8 show the classification experimental results. In Tables IV and V, the performance of classification for WF is best in comparison with WfL, WtR, and WE by using RMS or WL feature. That is to say, sEMG signal for WF is relatively strong.

Compared with the performance between Fig. 7 and Fig. 8, accuracy of classification is higher by using RMS feature for four kinds of wrist motions. What is more, sEMG signal of the subjects vary from person to person. the variability of sEMG signals represent the subjects operational characteristics. According to the experimental results from experiment 1 and 2, it can be demonstrated the wrist motions can be recognized with higher accuracy by using the RMS feature.

TABLE IV
THE RESULTS OF WRIST GESTURE CLASSIFICATION FOR EXPERIMENT 2 BY USING RMS FEATURE.

Gesture	WtL	WtR	WE	WF
WtL	0.895	0	0	0
WtR	0	0.8	0	0
WE	0	0	0.85	0
WF	0	0	0	1

TABLE V
THE RESULTS OF WRIST GESTURE CLASSIFICATION FOR EXPERIMENT 2 BY USING WL FEATURE.

Gesture	WtL	WtR	WE	WF
WtL	0.88	0	0	0
WtR	0	0.75	0	0
WE	0	0	0.8	0
WF	0	0	0	1

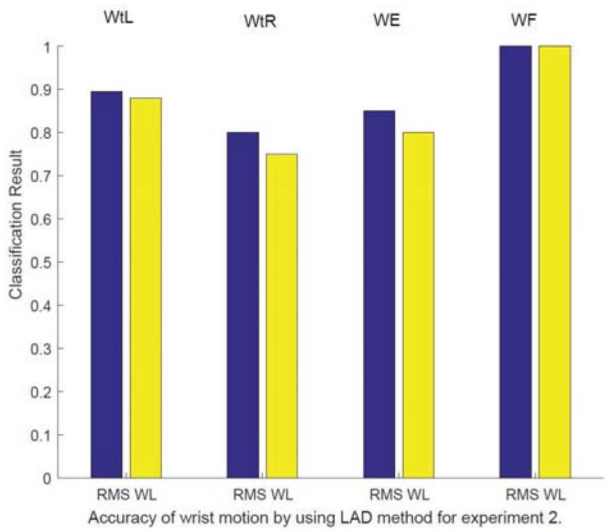

Fig. 8. Accuracy of wrist motion by using LAD method for experiment 2.

IV. CONCLUSION AND FUTURE WORK

A method based on sEMG signals is developed in this paper to recognize wrist motion of the surgeon. The classification method recognizes wrist motions by using RMS feature and WL feature. Compared with the WL feature, the accuracy of classification is higher when RMS feature are used as the input of LDA classifier. In the experimental results, it is showed that the proposed LDA approach can recognize the wrist motions successfully.

In the future work, several issues should be resolved. First, the different algorithms of feature extraction can reflect the different modes for the sEMG signals. The appropriate combination of feature extraction algorithms can effectively improve the classification accuracy of the motions. Therefore, integration of different feature extraction algorithms for the motion classification should be taken into consideration.

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