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FULL PAPER

A method of motion recognition based on electromyographic signals

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In a robot-assisted surgery, a skillful surgeon can perform the operation excellently through flexible wrist motions and rich experience. However, there are little researches about the relationship between the wrist motion and electromyography (EMG) signal of surgeon. To this end, we introduce a classification framework of wrist motion to recognize the common wrist motion of the surgeon based on EMG signals. Generally, surface EMG (sEMG) signal has been widely used in prosthetic hand control and medical clinical application. Hence, in this paper, we utilize sEMG signals to evaluate the wrist motions. Eight channels of sEMG signals are captured through a MYO armband from the forearm of the subject. Different kinds of features based on EMG signal, root-mean-square, waveform length, and autoregressive are used to recognize wrist motion through linear discriminant analysis method. We test the impacts on recognition performance from the different sEMG features and different sampling moving windows length. Experimental results have verified the recognition performance of the presented approach. It is validated that the RMS feature can achieve best recognition performance with all different sampling moving windows length in comparison with the WL feature and AR feature.

Keywords: motion recognition; electromyography signals; motion pattern

1. Introduction

As the development of control, information science and mechanism etc., robots provide more and more advantages in our life [1][2]. Especially, medical robots are widely utilized to the clinic operation, and rehabilitation [3][4]. In recent researches, electromyogram (EMG) signals are introduced to show the human's motor characteristics in the application of robots. In general, EMG signal implies the summation of motor unit action potentials from the human's muscle fiber [5][6]. Different muscles can generate various EMG signal for indicating the different motions. EMG signal has been widely utilized as the indicator of muscle activation [7], in EMG-based shared control for human-machine interaction [8][9], muscle signals powered wearable walking robots [10], and motion pattern recognition of human hand [11]. In this paper, we aim to recognize the wrist motion by using EMG signals and explore the impact on recognition performance by using different EMG-based features.

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With the developments of sensor technology, computer science and human-machine interface, the EMG-related technologies are greatly enhanced, especially, surface electromyogram (sEMG) signals are contributed to the applications in various areas, such as motion patterns recognition, clinic application in medicine [12], and EMG-based human-machine interaction [13][14]. In a word, EMG-based techniques have great potential deserving research in our lives. However, the traditional capture technologies of EMG signals need to implant the EMG sensors into the skin. It has some limitations in practice. Compared with traditional capture technologies of EMG signals, the capture of sEMG signals just need some electrode sensors are attached to the skin without implantation under the skin. It is a very convenient way to collect sEMG signals. Since the EMG signals can be captured and decoded the patterns of muscle activation feasibly, it has led to increasing research upsurge in the world [15][16][17]. For a skillful surgeon, they can perform excellently the complex operation through their wrist motion and rich experience. Due to surgeons always keep a gesture of fingers close together when they hold the instruments, the movements of hand mainly depend on the motion of wrist. In this process, we take common wrist motion of surgeon into consideration and explore the relationship of these motions and EMG signals.

For motion recognition, it is crucial to select correct feature(s). Many significant achievements have been demonstrated that proper EMG-based feature can enhance the recognition performance of motion [18][19][20]. Generally, time-domain features and frequency-domain features are widely used in EMG-based motion classification. In [21], mean absolute values (MAV) method were used to extract the feature information for the purpose of evaluation of muscle synergies. In time-dmain method, variable features of EMG signals could improve the accuracy of recognition for multiple finger motions [22]. In addition, multiple feature based on time-domain can make a difference in the aspects of enhancing the performance of classification. In [23], the authors utilized five different time-domain features to recognize the motion patterns and obtained a satisfactory experimental results. Bhattacharya *et al.* developed a effective multi-feature selection algorithm to detect the motion patterns and to control limb prosthses [24]. Additionally, the researchers are very interested in selection of different kinds of EMG signals' feature. Moreover, in [25], in order to improve the recognition accuracy of lower limb motion, a top and slope method was used to characterize the sEMG signal's feature. It is concluded that EMG-based characteristics, such as time-domain features, can be used as the feature to indicate the characteristics of EMG signals and can be utilized in the human-machine application as an indicator.

After obtaining the proper features of EMG signal, the key work is how to recognize the motion patterns by using these features. For the purpose of enhancing the classification accuracy of the motion, more and more researchers have proposed many feasible approaches in recent decades [26][27]. In [28], the authors proposed an integration method of Bayesian and neural networks (NN) to classify the motions for human-robot interfaces. The authors developed an optimized NN method to evaluate motion pattern by using EMG signals [29]. As the development of fuzzy theory, some achievements of fuzzy logic were developed to deal with the problems of motion patterns classification [30]. Since the difference of human subjects' characteristics, some researchers try to recognize the motion from the aspects of independent of subjects. In [31], a decoding model method wasused to decode the patterns information of wrist and hand motions. Recently, deep-learning techniques have promoted the development of machine learning applications, and EMG-based area is no exception. For example, the deep learning approach was utilized to classify the sleep stage [32]. In [33], a novel convolutional neural network (CNN) was proposed to decode the wrist movements based on the characteristics of raw EMG signals. Indeed, these methods are used to recognize the motion patterns successfully. However, those significant achievements are still hard to be utilized in real applications. In this work, we explore to find a simple framework to for recognizing the motion patterns in order to improve the analysis efficiency. Based on the inspiration of above-mentioned feature selection and motion recognition approaches [34][35], we develop a framework to explore the relationship between wrist motion patterns and EMG signals for surgeon.

Specially, the main contribution can be concluded as below.

- A recognition framework of wrist motion for surgeon is developed to integrate linear discriminant analysis (LDA) method with three different EMG-based features.
- An analysis of influence of different sEMG signals' feature and different sampling moving window length for recognizing the motions of surgeon. The proposed framework can effectively recognized the wrist motion patterns by a simple classifier.

The rest paper's structure is organized as following. Section 2 presents the presented approach in terms of data preprocessing, feature selection, and classification. Section 3 validates the developed approach and details the results in terms of the influence of different feature and sampling moving window length for the motion recognition. Section 4 concludes the conclusion and provides an outlook of the future of motion recognition.

2. Proposed Method

In this paper, four different kinds of typical wrist motions for surgeon are considered. This work aims to explore the relationship of wrist motion patterns and EMG signals. As shown in Fig. 1, it shows the proposed framework of the wrist motions recognition for surgeon. Specially, it mainly includes signals preprocessing module and motion recognition module. As shown in the figure, it should be preprocessed the captured raw sEMG signals at first, then we extract the sEMG signals feature to classify the wrist motion. Through this framework, we can recognize the specific motion pattern of surgeon.

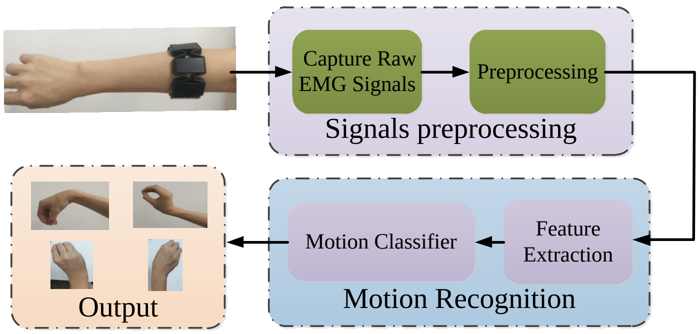


Figure 1. The wrist motion framework.

2.1 *Data Preprocessing and feature selection*

As shown in Fig. 2, it is seen that a human subject wears MYO armband on subject's forearm to capture sEMG signals with 200 Herz. The MYO armband has eight detection channels. Correspondingly, we can obtain 8-channel sEMG signals. In this paper, four common wrist motions of surgeon are considered, therefore we define the different wrist motion M as below:

$$M = \begin{cases} M1 & \text{wrist flexion.} \\ M2 & \text{wrist extension.} \\ M3 & \text{wrist to the left.} \\ M4 & \text{wrist to the right.} \end{cases} \tag{1}$$

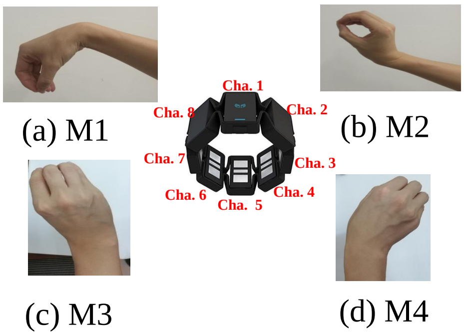


Figure 2. Four kinds of wrist motions.

We utilize root mean square (RMS) feature [36][37], waveform length (WL) feature [38][23] and autoregressive model (AR) feature [39][40] as the feature of sEMG signals. Representations of RMS, WL, and AR can be represented as below.

$$RMS(j,k) = \sqrt{\frac{1}{L_{rms}} \sum_{i=1}^{L_{rms}} x_i^2}. \tag{2}$$

where L_{rms} denotes the sampling moving window's length of RMS feature. x_i is the captured raw sEMG signals. $RMS(j,k)$ is the feature value in j-th channel for the k-th sample.

$$WL(j,k) = \frac{1}{L_{wl}} \sum_{i=1}^{L_{wl}} \Delta x_i. \tag{3}$$

where $\Delta x_i = x_i - x_{i-1}$. L_{WL} denotes the sampling moving window's length of WL feature. $WL(j,k)$ represents the feature value of WL in j-th channel for the k-th sample.

$$AR(j,k) = \frac{1}{L_{ar}} \sum_{i=1}^{\gamma_{ar}} a_i x_{k-i} + \varepsilon_k \tag{4}$$

where γ_{ar} is order of AR coefficients. a_i is the coefficients. ε_k denotes the residual white noise. We define L_{ar} is the sampling moving window's length of AR feature for the k-th sample.

Based on Eqs. (2)-(4), the feature of sEMG signals can be defined as

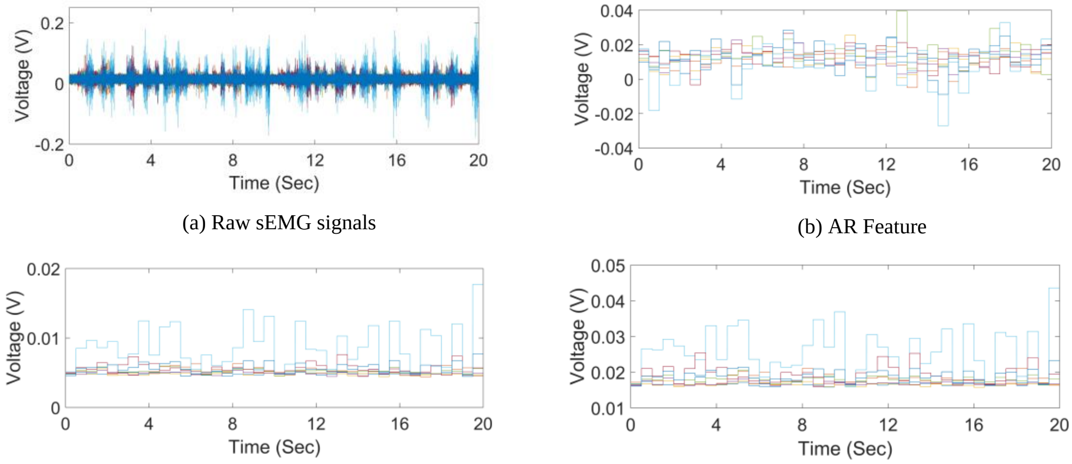
$$\mathbf{RMS} = [RMS1,\ RMS2,\ ...,\ RMSj,\ ...,\ RMS8] \tag{5}$$

$$\mathbf{WL} = [WL1,\ WL2,\ ...,\ WLj,\ ...,\ WL8] \tag{6}$$

$$\mathbf{AR} = [AR1,\ AR2,\ ...,\ ARj,\ ...,\ AR8] \tag{7}$$

where **RMS** demote the RMS feature of sEMG signals. $j = 1,\ 2, ...,\ 8$ represent the sEMG signals' capture channel. **WL** demote the WL feature of sEMG signals. **AR** demote the RMS feature of sEMG signals.

As shown in Fig. 3, it can be seen that there are eight channels sEMG signals and their corresponding feature. Fig. 3 (a) indicates the characteristic of raw sEMG signals. Figs. 3 (b)-(d) are the AR, WL, and RMS feature of sEMG signals, respectively.



(a) Raw sEMG signals (b) AR Feature

(c) WL Feature (d) RMS Feature

Figure 3. sEMG signals preprocessing.

Therefore, the input of the proposed framework can be defined as

$$\mathbf{I} = [\mathbf{F}_I, \mathbf{M}]^T \tag{8}$$

where $\mathbf{F}_I = [\mathbf{RMS}\ \mathbf{WL}\ \mathbf{AR}]$. $\mathbf{M} = [M1\ M2\ M3\ M4]$.

2.2 *Classification*

In this classification section, LDA method is introduced to recognize the wrist motion with related to RMS feature, WL feature, and AR feature. As above mentioned, $M_i = [M1,\ M2,\ M3,\ M4]$ is the wrist motion's recognition results. $F_I = [RMS,\ WL,\ AR]$ denote the sEMG signals' feature.

Inspired by [41][42], posterior probability $p(M_i|F)$ is presented as below:

$$p(M_i|F_I) = \frac{p(M_i)p(F_I|M_i)}{p(F_I)} \tag{9}$$

where $p(F_I)$ denotes the prior probability of F_I. When we get the maximum of posterior probability $p(M_i|F)_{max}$, the recognized wrist motion $M_i|_{p=p(M_i|F)_{max}}$ is determined.

$p(F_I|M_i)$ denotes the contingent probability. We assume that contingent probability $p(F_I|M_i)$ obey the multivariate probability distribution. And one has

$$\begin{aligned} p(F_I|M_i) = & \frac{1}{\sqrt{(2\pi)^r det(C_m)}} \\ & \exp\{-\frac{1}{2}(F_I - \hat{\mu}_i)^T C_m^{-1}(F_I - \hat{\mu}_i)\} \end{aligned} \tag{10}$$

Table 1. The experimental parameters.

Experiment	Experiment 1	Experiment 2
Size of training set	20000*8	20000*8
Size of testing set	500*8	400*8
Types of feature F_I	$RMS,\ WL,\ AR$	$RMS,\ WL,\ AR$
order of AR coefficients γ_{ar}	4	4
Size of moving window L	20, 50, 100, 500	20, 40, 50, 80, 100, 200

where r is the number of feature for sEMG signals. $\hat{\mu}_i$ denotes the mean vector with related to M_i. C_m represents the covariance matrix of wrist motions $M_1,\ M_2,\ M_3, M_4$.

Take the logarithm of both sides on Eq. (10), the maximum of posterior probability $p(K_i|F)_{max}$ can be determined. By using the linear discriminant function (LDF) $\hat{\delta}(k)$ which is introduced as

$$\hat{\delta}(k) = F_I^T \hat{\mu}_g + \hat{c}_g \tag{11}$$

where $\hat{\mu}_g = C_m^{-1}\hat{\mu}_k$. $\hat{c}_g = -\dfrac{1}{2}\hat{\mu}_k^T C_m^{-1}\hat{\mu}_k$

At last, the recognition results of wrist motion can be obtained after maximizing the LDF $\hat{\delta}(k)$.

3. Experiments and results

In order to verify the performance of the presented approach, four comparative experiments are performed. The experimental configuration is presented as below:

- *Hardware configuration.* MYO armband with 8 sensors (200 Hz) is used to capture the raw sEMG signals. A working station configurates a i7-3770T CPU with 2.50GHz, 12 GB internal storage for the experiments.
- *Software environment.* MATLAB and Visual Studio 2013 are operated on Windows 7 operation system. MATLAB is used to analyse the experimental data. Visual Studio 2013 is utilized to capture sEMG signal through bluetooth communication with the MYO armband.

There are two healthy subjects with age 22-30 years old are taken part in the experiments. The subjects are requested to do the motions with maximal angle in a sequence of M1, M2, M3, and M4. It is noted that the position of MYO for the 2 subjects is same. They are asked to finish every wrist motion two times within two minutes. The subjects are informed of the details of the experiment in advance. In the process of experiments, they are requested to take a break with thirty minutes. Three features $RMS,\ WL,\ AR$ are tested to estimate the recognition performance for each motion. Furthermore, we discuss the influence of different length of sampling moving window. The experimental parameters are presented in Table 1.

For validating the effectiveness of the presented approach, accuracy (ACC) is introduced in this paper, it can presented as

$$ACC = \frac{Sum_{correct}}{Sum_{total}} \tag{12}$$

where $Sum_{correct}$ is the number of correct recognized wrist motion. Sum_{total} denotes the total number of sampling data.

Table 2. Classification results of wrist motions with RMS feature, WL feature, and AR feature with moving window length $L = 100$ in experiment 1.

Gesture/Feature	RMS	WL	AR
M1	0.8244	0.7843	0.4102
M2	0.8091	0.7435	0.3838
M3	0.7551	0.7219	0.4080
M4	0.7829	0.7194	0.3502

Table 3. Classification results of wrist motions with RMS feature, WL feature, and AR feature with moving window length $L = 50$ in experiment 2.

Gesture/Feature	RMS	WL	AR
M1	0.8325	0.7550	0.4010
M2	0.7944	0.7194	0.3374
M3	0.81331	0.7188	0.3176
M4	0.7904	0.7301	0.3466

3.1 *Influence of different feature*

In the experiments, we test the influence of different feature using RMS, WL, and AR.

Fig. 4 and Table 2 show the experimental results of experiment 1 with sampling moving window length $L = 100$. The recognition accuracies of M1 and M2 are almost the same when using RMS feature. It can be seen that RMS feature achieves the best recognized performance for each wrist motion. The performance of recognition is the worse when using WL feature. AR feature has the worst performance of recognition in comparison with those of RMS feature and WL feature.

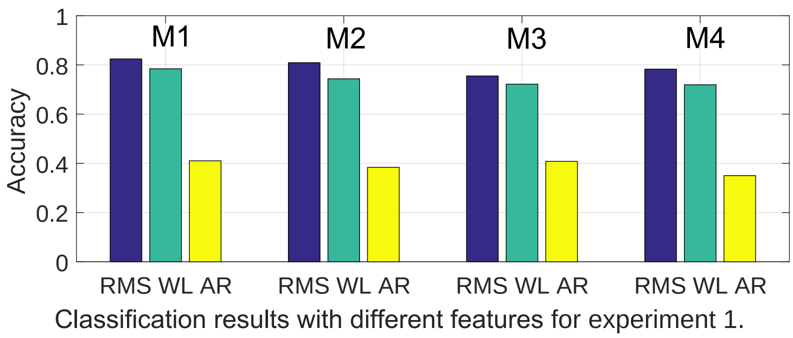


Figure 4. Classification results of wrist motions with different features for experiment 1.

In experiment 2, Table 3 and Fig. 5 show the classification results. It can be seen that the classification result for M1 is best with RMS feature, WL feature, and AR feature. The recognition accuracies of M2 and M4 are almost the same when using RMS feature and AR feature. For each wrist motion, it can be concluded that the RMS feature achieves the highest recognition accuracy.

Taken together, classification accuracy is the highest with RMS feature in Figs. 4-5. In addition, the recognition performance is different when the subjects perform a same motion. For example, it can be seen that the recognition performance of experiment 2 is better than that of experiment 1 according to the experimental results from Tables 2-3 for wrist motion M3. That is to say, the strength of sEMG signals of experiment 2 is stronger than that of experiment 1 for Motion M3 since of the muscle activation is different between two different subjects.

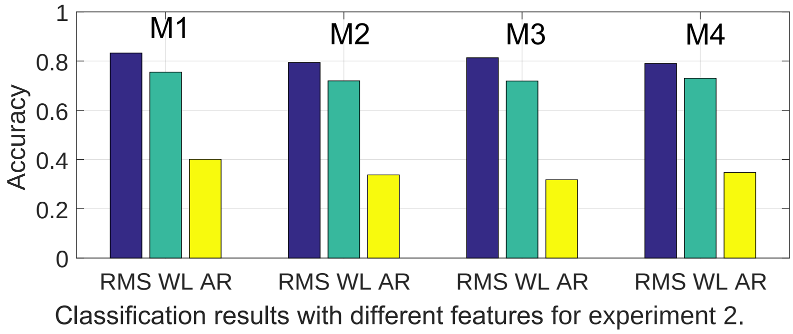


Figure 5. Classification results of wrist motions with different features for experiment 2.

3.2 *Influence of different moving window length*

In this section, we mainly analyse the influence of different moving window for the recognition performance.

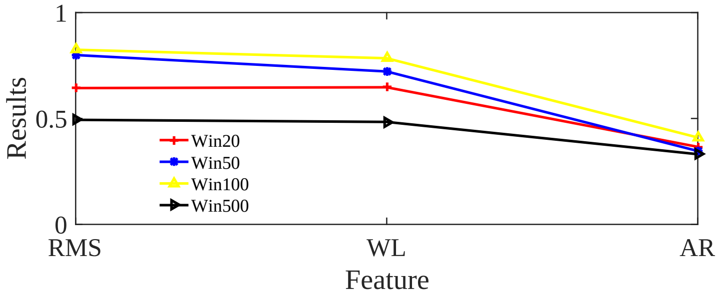


Figure 6. Accuracy of M1 by using different feature for experiment 3.

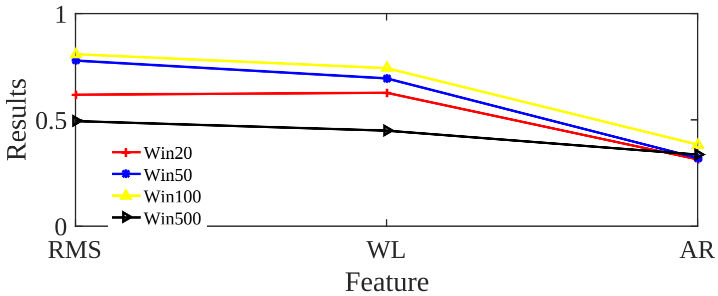


Figure 7. Accuracy of M2 by using different feature for experiment 3.

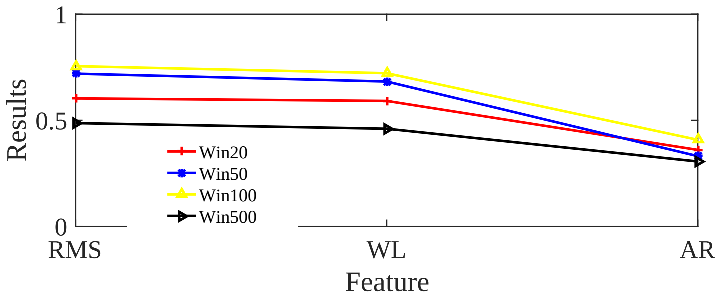


Figure 8. Accuracy of M3 by using different feature for experiment 3.

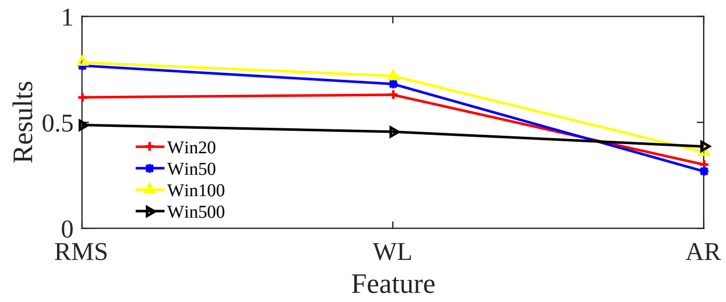


Figure 9. Accuracy of M4 by using different feature for experiment 3.

In experiment 3, we verify the recognition performance with moving window length $L = 20$, $L = 50$, $L = 100$, and $L = 500$. Figs. 6-9 show the recognition accuracy of different moving window length for each wrist motion. For wrist motions M1-M4, the recognition accuracies are highest when the length of moving window is 100 no matter which feature is used. However, the performance is worst when the moving window length is 500. In this sense, the accuracy gets higher as the length of moving window increases when $20 \leq L \leq 100$. It can be seen that the recognition performance with RMS feature is best when using RMS feature and WL feature for M1-M4.

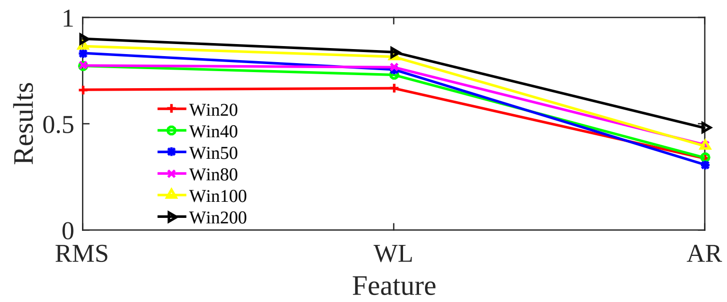


Figure 10. Accuracy of M1 by using different feature for experiment 4.

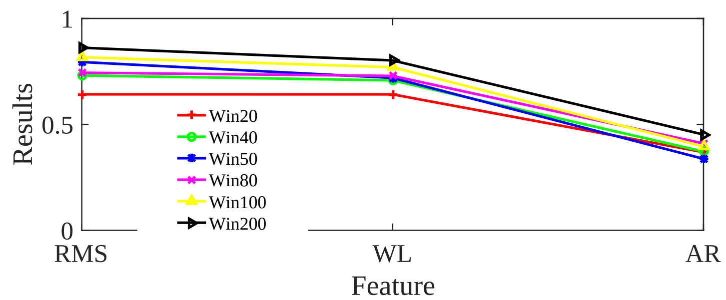


Figure 11. Accuracy of M2 by using different feature for experiment 4.

For experiment 4, the recognition performance with moving window length $L = 200$ is best in comparison with the moving window length are $L = 20,\ 40,\ 50,\ 80,$ and 100. When the moving window is determined, the recognized accuracy are highest when using the RMS feature. In this experiment, it can be seen that the accuracy is higher as the moving window length increases. In this sense, the accuracy has a relative positive correlation with the length of moving window for M1-M4 when $20 \leq L \leq 200$.

Based on the above-mentioned analysis, it is essential to analyse the impacts of the length of moving window and different feature of sEMG signals . From the experimental results of experiments 1-4, it can be concluded that the recognition performance is best when using RMS

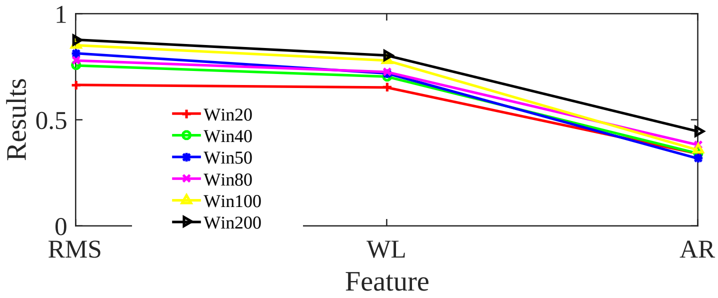


Figure 12. Accuracy of M3 by using different feature for experiment 4.

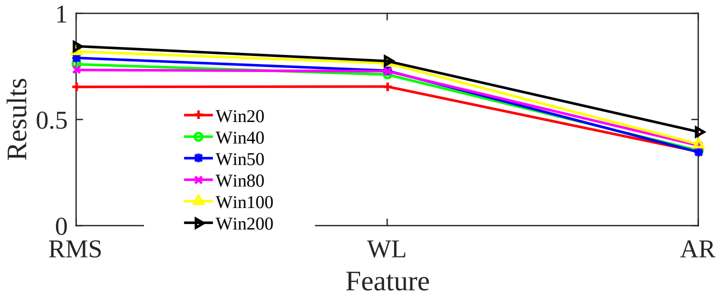


Figure 13. Accuracy of M4 by using different feature for experiment 4.

feature. The influence of different length of moving window should be analysed according to the actual sEMG signals and its feature. It is noted is that the optimal window length changes from person to person, and also a qualitative observation is that the best or most efficient window length cannot be too small neither too big.

4. Conclusion and discussion

We develop a wrist motion recognition framework based on sEMG signals in this work. RMS, WL, and AR are used as the feature of sEMG signals. These features are used as the input sample to train the classifier by using the LDA approach to recognize different wrist motions. Four comparative experiments are performed to validate the effectiveness of the developed method. The experimental results demonstrated that the proposed framework with RMS feature can obtain the best recognized performance in comparison with that of WL feature and AR feature. Furthermore, there is a relative positive correlation between the length of sampling moving window and the recognition accuracy within certain range. In this sense, the researcher can choose a relative greater length of sampling moving window for motion recognition.

Although MYO software provides the own function to detect the hand gesture, but it is very different between its basic motions of MYO's demo and the common wrist motions of surgeon. Since surgeon always keeps a gesture of fingers close together when they hold the instruments, the movements of hand mainly depend on the motion of wrist. We mainly consider four common motions $M1, M2, M3,$ and $M4$. Actually, other wrist motions can be recognized. In this work, we collect the common wrist motions of surgeon, and extract the EMG signals in a self-made way, so the size of sample data is limited. In this sense, in future work, we will consider the larger size of sample data and achieve a better performance, i.e. accuracy and variance. Furthermore, more different feature extraction algorithms and integration of those feature extraction algorithms would be considered to reflect the robustness of sEMG signals' feature. Due to the sampling data sets become larger and larger, some dimensional reduction techniques and deep learning method will be introduced to deal with the problem of data preprocessing. Since the characteristic of sEMG signals is different from person to person, the difference of individuals will be estimated in statistics, we will add the different motions of more subjects and test thedeveloped approach in the extensively recognized data set [43]. In addition, multimodal infromation and the application of EMG should be considered in more actual areas, such as [44][45][46][47].

Acknowledgements

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