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Improving the myoelectric motion classification performance by feature filtering strategy

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***Abstract*—Currently, electromyography pattern-recognition (EMG-PR) based myoelectric prosthesis is widely used in many laboratories worldwide. In the EMG-PR based method, EMG features would be extracted from the EMG signals and used to predict the user's motion intent. However, in clinical use, many interferences such as muscle fatigue, electrode shift and so on, were usually introduced to degrade the feature quality, which would decay the performance of a trained EMG-PR classifier in identifying motion intentions. In this study, a novel preprocessing strategy, feature filtering, was proposed to improve the performance of EMG-PR based classifier in motion classification. Three feature filtering methods of mean filter (MF), Median filter (MDF), and Weighted Average filter (WAF) were designed to investigate the effectiveness of this strategy. By analyzing the results of six able-bodied subjects, it demonstrated that the motion classification performance could be improved by using the feature filtering strategy, achieving the increments of 4.4%, 2.8%, and 3.5% for MF, MDF and WAF, respectively. These preliminary results suggest that using the feature filtering strategy may enhance the robustness of EMG-based myoelectric control.**

I. Introduction

Electromyography Pattern Recognition (EMG-PR) control method is an advanced and intelligent technique and have been investigated in many laboratories worldwide [1-4]. This method assumes that the EMG signals contain rich information of user's motion intent that can be extracted and represented in a set of features, especially, the feature set should be repeatable for the same motion task and discriminative between different tasks [4]. In the traditional EMG-PR based multifunctional prosthetic system as shown in Fig.1, EMG signals were firstly collected from the skin surface of the residual muscle. And then features are extracted from the collected data and then fed into the trained classifier. Lastly, the classifier will select the motion whose trained pattern best match the current extracted features as the output of the prosthetic controller. Therefore, the performance of EMG-PR method greatly depends on the high quality of the features and good classification algorithms.

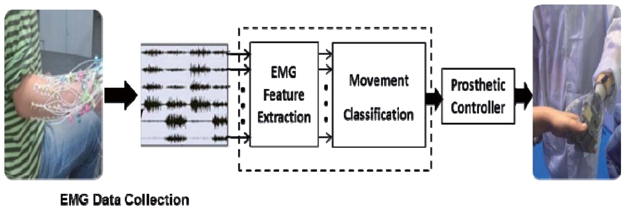

Figure 1. Conventional EMG-PR control scheme for multifunctional prosthetic systems

Some previous studies investigated the effects of the classification algorithms and the input features on the classification performance [5-7]. The results demonstrated that the extracted features have a more significant impact. A number of attempts and efforts have been made to extract the proper features from sEMG signals for accurate motion classification for several decades [8, 9]. A feature sets of four time-domain features, namely, mean absolute value (MAV), waveform length (WL), zero crossings (ZC), and number of slope sign changes (SSC) proposed by Hudgins et al., [4] have gained wide application since they are simply calculated, requiring small memory space, and short computation time. However, after several years of efforts, there are still many obstacles for EMG-PR based multifunctional myoelectric prostheses to be commercially available for clinical use. One of the major challenges is that the existing EMG-PR based prosthetic devices are not robust enough for real life applications [10-12].

During the clinical use, many interferences [13-15] such as muscle fatigue, electrode shift, change of arm position, variation of force levels, and unwanted movements (UMs), would be introduced to increase the sEMG signal variability, which will degrade the extracted feature repeatability and accordingly decay the performance of a trained EMG-PR classifier in identifying movement intentions. Therefore, improving the robustness of the extracted feature might be one major task to promote the clinical use of the EMG-PR based multifunctional prostheses.

In this study, a novel preprocessing strategy, filtering the features before they fed into the classifier, was proposed to reduce the feature variation caused by the EMG signal noise that was introduced during motion activity. To realize this strategy, three simple filtering methods, namely Mean filter, Median filter and Weighted Average filter were designed. respectively, to investigate the effectiveness of this strategy. Six able-bodied subjects and six commonly used hand/wrist motions were employed in this work to investigate the effectiveness of the three filtering methods respectively.

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II. METHODS

A. Subjects

Six able-bodied subjects were recruited in this study. The age of the subjects ranged from 23 to 26 years and they are all right-hand dominated. The experimental protocols were approved by the Shenzhen Institutes of Advanced Technology, Chinese Academy of Sciences. All subjects provided permission for publication of photographs for scientific and educational purposes.

B. Data acquisition

Five EMG electrode of a wireless acquisition system (Delsys Inc., Boston, MA, USA) was used to record EMG data. For each subject, the five electrodes were placed over the main flexor and extensor bundles of the right forearm, as shown in Fig.2. All the collected EMG signals were passed through a band-pass filter with cut-off frequencies of 10 and 500 Hz, and the sampling rate was 1024Hz.

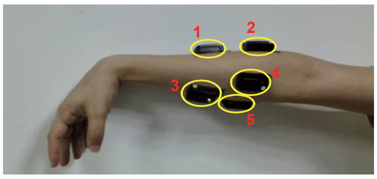

Figure 2. Placement of electrodes for EMG data recording.

Six motion classes of hand open (HO), hand close (HC), wrist extension (WE), wrist flexion (WF), wrist pronation (WP), and wrist supination (WS) were designated in this study. For each subject, the experiment comprised two sessions. In each session, subjects were asked to perform the motions by a prepared video prompt. Each motion class was performed 10 times at the mederate force level and held for 4 s one time. To avoid muscle fatigue, there is a 5 s rest between two motions and a 3-min rest between two sessions.

C. Feature extraction

The sEMG signal analysis was performed offline with Matlab (*The Mathwork Inc.*). The EMG signals recorded of the first session were used as the training set, while the EMG signals recorded of the second session were used as the testing set. And then the signal recordings were segmented into a series of 150-ms analysis windows with an increment of 100 ms. And four commonly used TD features of mean absolute value (MAV), waveform length (WL), zero crossing (ZC), and number of slope sign changes (SSC) were extracted from each analysis window [4, 16-18].

D. Feature filtering

As shown in Fig.3, the extracted features would be filtered before fed to the phase of pattern classification. In this study, three simple filtering methods namely 3-order Mean filter (*MF-3*), 3-order Median filter (*MDF-3*), and 3-order Weighted Average filter (*WAF-3*) were proposed to enhance the quality of the extracted features.

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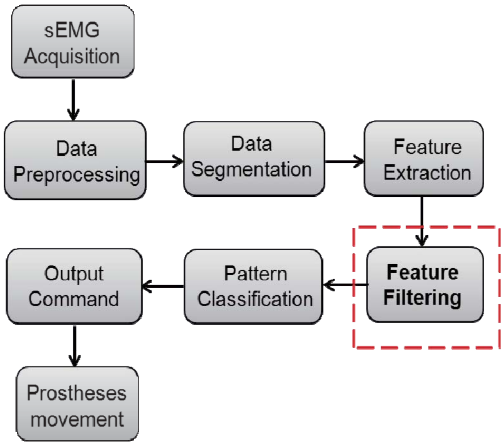

Figure 3. Scheme of the proposed EMG-PR based prosthetic control.

(1) *3-order Mean filter (MF-3)*

In the WAF-3 method, the current filtered feature y_i is the mean value of the features extracted from the previous three and the current one analysis windows.

$$y_i=\frac{1}{4}\sum_{j=i-3}^{i}x_j,\qquad i>N \tag{1}$$

Where, x_j denotes the feature extracted from the j^{th} analysis window.

(2) *3-order Median filter (MDF-3)*

In the *MDF-3* method, the extracted features of the previous three and the current one analysis window were sorted in decreasing order to obtain the ranked sequence X as in Eq.(2) . And then, the median value y_i was computed based on the mean of x_2' and x_3' in Eq. (3).

$$X=\{x_1',x_2',x_3',x_4'\},\quad in\ which\ x_i'\succ x_{i+1}' \tag{2}$$

$$y_i=\frac{x_2'+x_3'}{2} \tag{3}$$

(3) *3-order Weighted Average filter (WAF-3)*

In the *WAF-3* method, a weighted factor was introduced for each feature, and the filtered feature y_i is the average value of the weighted features as shown in Eq.(4). In this study, the weighted factors were designed as a geometric progression, the sum of which is 1, as expressed mathematically in Eq. (5).

$$y_i=\frac{1}{4}\sum_{j=i-3}^{i}x_j f_j,\qquad i>3 \tag{4}$$

$$\begin{cases} f_j=f_i q^{|i-j|} \\ \sum_{j=i-3}^{i} f_j=\frac{f_i(1-q^3)}{1-q}=1,\quad q\neq 1 \end{cases} \tag{5}$$

Where q is the common ratio of the weighted factors. And the f_j can be computed as a function of q in Eq. (6). In this study, the q was set as 0.5, therefore, the filtered feature y_i can be written as Eq. (7).

$$f_j = \frac{1-q}{1-q^3} \times q^{|i-j|} \tag{6}$$

$$y_i = \frac{1}{4} \cdot \frac{1-1/2}{1-(1/2)^3} \cdot \sum_{j=i-3}^{i} x_j \times (1/2)^2 \tag{7}$$

E. Motion classification

The Linear Discriminant Analysis (LDA) algorithm [17] was used in this study for the motion classification. The performances was assessed by the metric of classification accuracy in Eq. (8).

$$\text{Classification Accuracy} = \frac{\text{Number of correctly classified samples}}{\text{Total number of testing samples}} \times 100\% \tag{8}$$

III. Results

Fig.4 depicts an example of zero crossings extracted from a 4 seconds (39 analysis windows) EMG recording of the PG motion class. It can be seen from Fig.4 that the raw feature curve has high variations in its peaks and troughs, and such variations were smoothed by using the three proposed filtering methods. Additionally, it can be seen that the feature curves obtained by the methods of MF and MDF were smoother than that obtained by WAF.

The average motion classification accuracies across the six able-bodied subjects obtained by different filters were shown in Fig.5, where the average accuracy was 92.4% for the raw features, and increased to 96.8%, 95.2%, and 95.9% respectively by using *MF-3*, *MDF-3* and *WAF-3*.

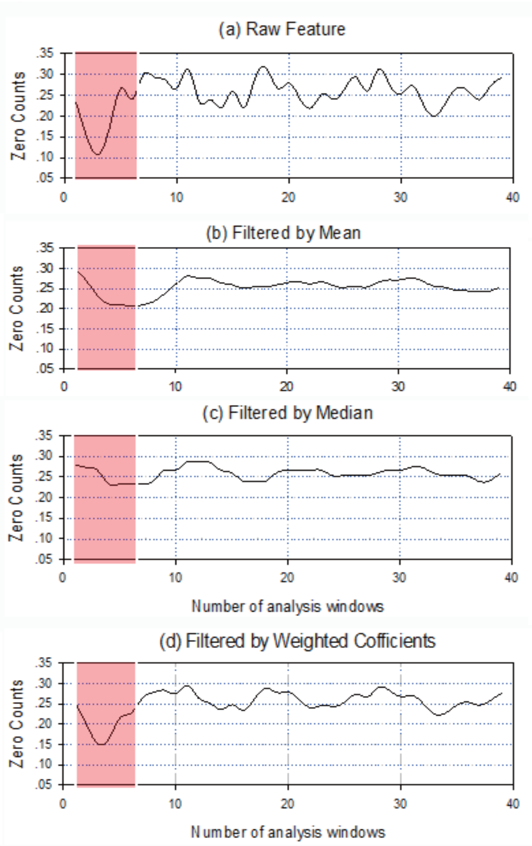

Figure 4. Classification accuracies of different filters across the six able-bodied subjects

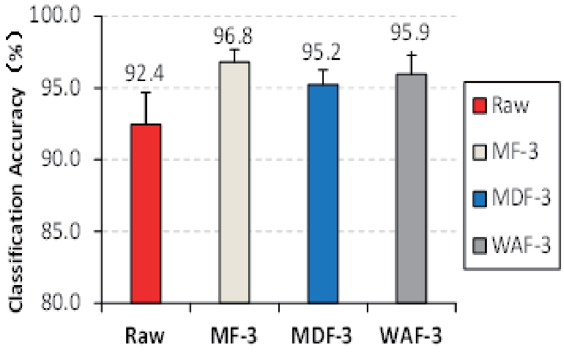

Figure 5. Classification accuracies of different filters across the six able-bodied subjects

Further, the classification accuracy of each motion was illustrated in Table 1. It can be seen from Table 1 that the classification accuracies of all the six motion classes were obviously increased by using the three feature filtering methods. Especially, the motions of HO, which had the lowest classification accuracies of 86.1% by raw features among the six motion classes, achieved the improvements of 9.2%, 6.9%, and 7.9% in classification performance respectively by *MF-3*, *MDF-3* and *WAF-3*. In addition, it can be observed that among the three type of filters, the method of *MF-3* achieved the best performance.

An example of classification outputs obtained by using the raw features and the three filtering methods was shown in Fig.6, where each motion class had the length of 4s. The predict outputs of the classifier are denoted by blue lines, while the true (target) motion classes are shown in red lines, and the misclassification are visible as spikes in the class outputs. It can be seen from Fig.6 that, there were many erroneous outputs occurred by using the raw features, especially for the motion of WS, about 20% samples were misclassified as HO. However, when using the three feature filtering methods, these misclassifications are greatly reduced.

IV. Discussion

Enhancing the robustness of control performance is a critical issue for clinical application of EMG-PR based multifunctional prosthetic device and has not been completely solved yet. The four TD features of MAV, WL, ZC, and SSC were commonly used in EMG-PR based motion classification. However, many previous studies reported that the motion classification accuracy achieved by using these TD features was usually influenced by various interferences in clinical application. In this study, a novel preprocessing strategy that filtering the features before the stage of classification, was proposed to reduce the feature variation.

The results of this study showed that the motion classification performance could be improved by using the filtering methods. Especially, the motions that were more difficult to be identified by using raw features achieved the greater improvement, e.g. the motion of HO which had the lower classification accuracy of 86.1% by using the raw features, achieved the highest increment of 9.2% among the six motions by using the feature filtering strategy. Additionally, the presented results in Fig.5 and Fig.6 showed that the method of *MF-3* achieved the higher classification accuracy than those of the *MDF-3* and *WAF-3*.

Table 1. Classification accuracies of the six movements across the able-bodied subjects.

Subjects	Hand Movements		Wrist Movements			
	HO	HC	WE	WF	WP	WS
Raw	86.1±3.1	94.7±3.5	94.5±2.6	95.2±3.1	92.1±5.9	92.3±4.6
MF-3	95.3±2.4	97.0±2.9	96.1±1.8	96.9±1.8	97.6±2.2	97.7±3.3
MDF-3	93.0±2.7	95.8±3.2	95.2±1.9	96.0±1.7	95.7±2.8	95.2±3.3
WAF-3	94.0±3.0	96.0±3.8	95.8±3.3	96.5±2.2	96.4±1.8	96.5±4.0

It may be demonstrated from the results that, the feature filtering method of *MF-3* had the better performance in improving the quality of EMG features.

Additionally, in Fig.6 it was clearly seen that the misclassified outputs of the raw features would be greatly reduced by using the feature filtering methods. However, in the classification outputs obtained by *MF-3*, it can be observed that some samples of WF were misclassified as WS. It is similar to the classification outputs obtained by *WAF-3*, where some WE samples were misclassified as HO. These results might be reasonable, because even if the function of a filter is to reduce the signal noise, it will inevitably attenuated some correct signal variations, especially at the contraction onsets and ends. This misclassification problem was also encountered in some previous studies [19, 20] in which different threshold approaches were proposed to minimize the false activations, however, some correct activations below the threshold would be rejected.

Above all, these preliminary results suggest that the proposed feature filtering strategy would be promising in improving the EMG-PR based motion classification performance. However, it should be noted that only six able-bodied subjects were recruited in this pilot study. In future work, more subjects including amputees with different amputation levels would be recruited to evaluate the feasibility of the feature filtering strategy in EMG-PR based motion classification. Additionally, the effect of filter order on the filtering performance, which is an important issue in designing a filter, would be investigated in the future work.

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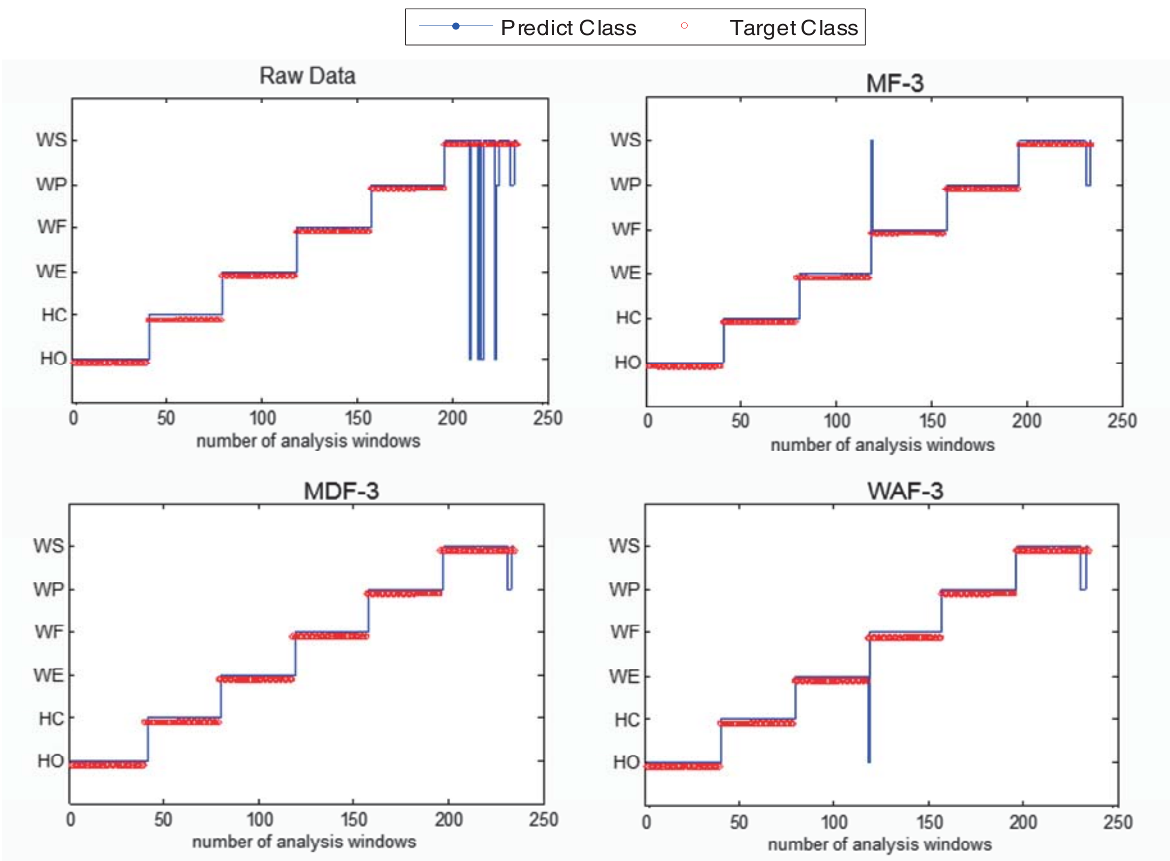

Figure 6. Example of correcting erroneous decision output by using different feature filtering methods.

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