Effects of non-training movements on the performance of motion classification in electromyography pattern recognition

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Abstract— **In electromyography pattern-recognition-based control of a multifunctional prosthesis, it would be inevitable for the users to unintentionally perform some classes of movements that are excluded from the training motion classes of a classifier, which might decay the performance of a trained classifier. It remains unknown how these untrained movements, designated as non-target movements (NTMs) in the study, would affect the performance of a trained classifier in the control of multifunctional prostheses. The goal of the current study was to evaluate the effects of NTMs on the performance of movement classification. Five classes of target movements (TMs) and four classes of NTMs were considered in this pilot study. A classifier based on a linear discriminant analysis (LDA) was trained with the electromyography (EMG) signals from the five TMs and the effects of the four NTMs were examined by feeding the EMG signals of the four NTMs to the trained classifier. Our results showed that these NTMs were classified into one or more classes of the TMs, which would cause the unexpected movements of prostheses. A method to reduce the effects of NTMs has been proposed in the study and our results showed that the averaged classification accuracies of the corrected classifiers were above 99% for the healthy subjects.**

I. INTRODUCTION

Electromyograhy (EMG) signals from the residual muscles have been widely used as a useful control signal in multifunctional myoelectric prostheses for the individuals with limb amputations. Currently, most commercially available myoelectric prostheses are controlled by the amplitudes of surface electromyography (EMG) signals from a pair of agonist-antagonist muscles on residual limbs. It is well known that this conventional control method is limited in control of multiple degrees of freedom of movements and lacks of intuitive controls of prostheses [1, 2]. In order to improve the performance of multifunctional prostheses, EMG pattern-recognition-based (EMG-PR) control methods have been well applied by many laboratories worldwide [1-11]; these previous efforts have suggested that the EMG-PR approaches would have the potential to allow the limb amputees to intuitively operate their multifunctional prostheses. Unfortunately, the multifunctional myoelectric prosthetic systems with the EMG-PR-based control method still stay in the laboratories and do not become a reality. The major reason why no EMG-PR-based prosthetic systems are available yet for clinical uses might be that the current EMG-PR prosthetic systems might lack of reliability and robustness for the clinical uses.

Recently, a number of efforts have been made with an attempt to speed up the progress of getting the EMG-PR-based prosthetic systems from the laboratory to clinical applications[4-6, 8, 9, 12]. Different disparities between the laboratory states and clinical states for myoelectric prostheses have been addressed and investigated well, such as the influences of electrode shifting, muscle contraction variation, muscle fatigue, sampling rate of EMG signals, and arm position changes, on the movement classification performance for the EMG-PR-based algorithms. Another important issue in the use of multifunctional myoelectric prosthesis is the effect of unintentional classes of movements on the control performance. In the real-time use of EMG-PR-based prostheses, it would be impossible for the users to avoid doing any movement that is not included within the training motion classes of a classifier. As an example, suppose that an EMG-PR classifier is trained with EMG recordings for the classification of two classes of movements such as hand opening and closing. For the trained classifier, the hand opening and closing would be the target movements (TMs) and all other movements would be non-target movements (NTMs). In the practical application of the trained classifier, it is inevitable for users to unintentionally perform these NTMs that would cause the limb residual muscle contraction to generate EMG signals. The EMG signals from NTMs will be captured by the surface electrodes and fed into the trained classifier for movement identification in real-time control of a multifunctional myoelectric prosthesis. The classifier would classify the NTMs to either hand opening or hand closing. Obviously, these NTMs would decay the performance of a trained classifier in real-time use. Daisuke proposed a supervising mechanism for learning data set for adaptation to the individual variation of EMG signal[13]. However, it is still unknown how these untrained movements would affect the performance of a trained classifier in the control of multifunctional prostheses.

In the current study, the effect of NTMs on the classification performance of a movement classifier was investigated by EMG recordings from two able-bodied subjects. The classifier was built based on a linear discriminant analysis (LDA) and was trained with high-density EMG signals from the forearm muscles when the

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subjects were doing five classes of TMs. The effects of classes of NTMs were evaluated by feeding the EMG signals from the four NTMs to the trained classifier. And a training strategy was proposed to reduce the effect by including the NTMs in the training set with label of "no movement". This study would provide the useful guides to improve the classification performance of a movement classifier toward its practical applications in control of a multifunctional myoelectric prosthesis

II. METHODS

A. Subjects

In this pilot study, two able-bodied subjects (one male and one female with ages of 27 and 25 years, respectively) were recruited. The experimental protocols were approved by the Shenzhen Institutes of Advanced Technology, Chinese Academy of Science. And all subjects provided permission for publication of photographs for scientific and educational purposes.

B. Experiment and Data Acquisition

For each subject, 64 channels of EMG data were recorded with a high-density EMG system (*REFA 128, TMS international, the Netherlands*). The electrodes were evenly placed in an eight by eight grid over the whole forearm area, as showed in Figure. 1. The center-to-center distance between every two adjacent electrodes was about 1.5 cm.

a) front of the arm   b) back of the arm

Figure 1. Placement of electrodes for high-density EMG data colleciton.

Five TM classes and four NTM classes were considered in this study. The TM classes included two hand motions: hand open (HO) and hand close (HC) as well as two wrist motions: wrist pronation (WP) and wrist supination (WS), plus no movement (NM). The NTM classes consisted of two hand grasps, point grip (PG) and hook grip (HG), and two wrist movements, wrist extension (WE) and wrist flexion (WF). For each subject, the experiment involved two successive sessions. In each session, the subjects held each of the TM and NTM classes for 5 seconds and repeated 10 times, which were guided by a prepared video. There was a 4-second break between two consecutive movement contractions and was an about 3-min rest between the two sessions. Prior to the experiment, each subject had a 10-min practice to get familiar with the motion classes and the experimental procedure. All channels of EMG signals were passed through a band-pass filter (cut-off frequency from 10 to 500 Hz) and then sampled at a rate of 1024Hz.

C. Data analysis and reduction of the NTM impact

EMG signal recordings were analyzed offline with Matlab (*The Mathwork Inc*). A 50 Hz notch filter was used to further attenuate the power-line noises. The EMG recordings from the two sessions were concatenated producing a 100-second data set for each class of movements and then the data set were segmented into a series of 150-ms analysis windows with a 50 ms overlap. For each analysis window, four time-domain features, mean absolute value, waveform length, zero crossings, and number of slope sign changes, that are widely accepted as an effective representation for EMG classification by many previous researchers [1, 3-5, 7-9] were extracted. The extracted features were then used as the input of a linear discriminant analysis (LDA) classifier that was proved to have excellent performance in various motion classifications [1, 3, 4, 8, 9].

For each subject, the EMG features from the TM classes were used to train the LDA classifier. And then EMG features from the NTM classes were fed to the trained classifier which would label them as the nearest one of TM classes. In order to evaluate the effects of NTM classes on the classification of TM classes, we proposed a measure index called *impact ratio* which was the percentage of NTM samples identified as TMs. For the *i*th NTM class, its impact ratio was defined as:

$$I_{ij} = \frac{n_{ij}}{N_i} \times 100\,\% \quad (i = 1,2,3,4;\; j = 1,2,3,4,5) \tag{1}$$

Where I_{ij} is impact ratio of the *i*th NTM class to the *j*th TM class; N_i is the total number of movements of *i*th NTM class; n_{ij} is the movement number of counted a NTM class into a TM class.

A straightforward strategy to reduce the effects of the NTM was to make the prostheses keep static when NTM occurred, preventing undesired movements. Therefore, a method that included NTM in the training set of the classifier with label "no movement" was proposed in this study. Thus, for each subject, the original nine motion classes (five TM and four NTM) were combined into five classes (HO, HC, WP, WS, and Combined NM) . The performance of the newly trained classifier was measured by the index of classification accuracy, which is defined as:

$$A_i = \frac{n_i}{N_i} \times 100\,\% \quad (i = 1,2,3,4,5) \tag{2}$$

Where A_i is the classification accuracy of *ith* motion class, n_i is the number of correctly classified *ith* samples, and N_i is the total number of *ith* class motion.

III. RESULT

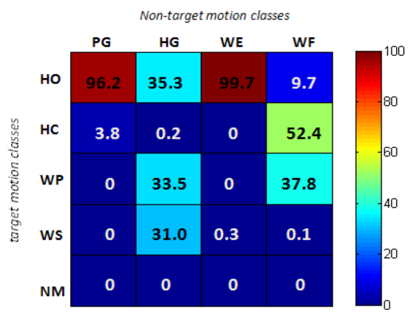
A. Effect of non-target movements

In the first phase of the experiment, the LDA classifier was trained by the TM classes and then the NTM classes were fed to the trained classifier to be categorized to the nearest TM class. From TABLE I, it can be seen that the five TMs were well identified by the trained classifier with classification accuracies all above 99%. The impact ratio of each NTM class was calculated and was shown in Figure 2. The most significant findings were that none of the NTM classes were classified as the no movement class. It was observed that the

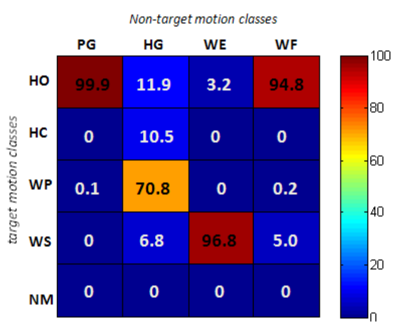
PG class was mostly classified into the HO target class. The percentage was 96.2% for female and 99.9% for male. There were differences between male and female for the classifications of the HG, WE and WF classes.

TABLE I. CONFUSION MATRIX FOR THE FIVE TARGET MOTIONS

	HO	HC	WP	WS	NM
HO	100		0	0	0
HC	0. 15	99.7	0.15	0	0
WP	0		100	0	0
WS	0	0	0	100	0
NM	0	0	0	0	100



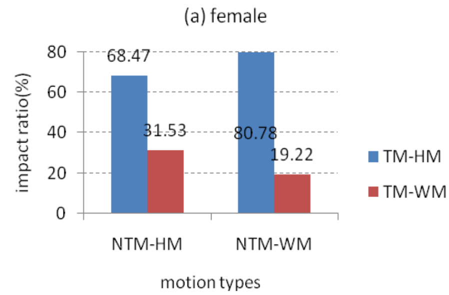
(a) female



(b) male

Figure 2. Impact ratio of non-target movements. The colums represent the four classes of non-target movements, and the rows represent the five target movements. The color bar indicate the percent of impact ratio

To examine the interactions of different motion types for the classification, the TMs and NTMs were grouped into hand motions (TM-HM and NTM-HM) and wrist motions (TM-WM and NTM-WM). The effects of different non-target motion types were shown in Figure. 3. It was observed from Figure. 3 that for both of the female and male subjects, the NTM-HM had greater probabilities to be identified as TM-HM, but the NTM-WM were more likely to be classified as the type of HM in target motions. This phenomenon was more evident for the female in Figure. 3, with 68.47% of the non-target hand motions classified as target hand motions and 80.78% of the NTM-WM categorized into target hand motions.



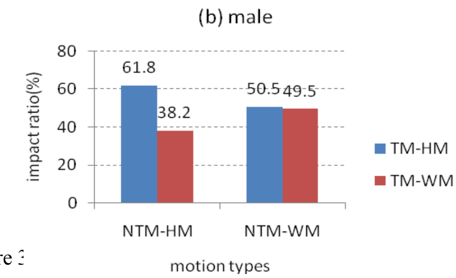
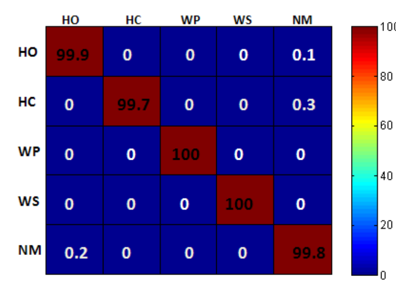


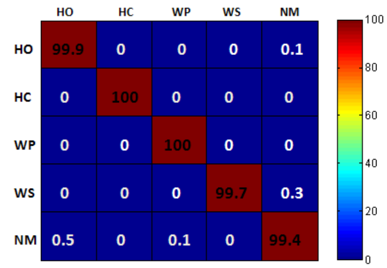
Figure 3 ... get and non-target motions.

B. Solution to reduce the effect of NTMs

To reduce the impacts of the NTMs on the control of the prosthesis, a practical strategy was to include some data of all undesired non-target motions in the training data with the label of no movement to avoid unwanted prosthesis movements. Five-fold cross validation was used to train and test the classifier, and the results were shown in Figure. 4. It was observed from Figure. 4 that the classification accuracies of the target motions (HO, HC, WP and WS) were above 99% for both of the subjects. Meanwhile, about 99.8% of the testing NTM samples were correctly classified to the new label (no movement) for the female (Figure 4(a)), and it was around 99.4% for the male (Figure 4(b)). The averaged accuracy (listed in TABLE Ⅱ) of all the motions for the two subjects was both above 99%.



(a) female



(b) male

Figure 4. Confusion matrix after the NTMs were included in the training with label of "no movement".

TABLE II. CLASSIFICATION ACCURACY MATRIX OF THE CORRECTED MOTIONS

Subject	HO	HC	WP	WS	NM	Average
Female	99.9%	99.7%	100%	100%	99.8%	99.88%
Male	99.9%	100%	100%	99.7%	99.4%	99.8%

IV. DISCUSSION

In this pilot study, we investigated the effect of NTMs on TMs. The preliminary results showed all of the NTM were classified as TMs rather than the no movement class (Fig.3), which suggested that the undesired motions made by the subjects would have a big impact on the target motions and therefore should be taken appropriate care of. Among all NTM, it is observed that the movement of PG was nearly completely classified to the HO class, suggesting that the temporal features of HO were most similar to the PG motion, at least for LDA classifier. However, for other motions such as the HG, there is no such unique target motion that matches it best. Instead, it can be classified to multiple target classes by different portions.

A direct and effective method to reduce the effects of the NTM is to categorize all the unexpected motions to no movement to prevent the prosthesis control system from producing unwanted movements. Even though huge differences may exist in the temporal features between NTM and no movements, the results of this study showed that the LDA classifier could correctly identify various NTMs as the new label after it is trained by including the NTM samples in the class of no movement, with a classification accuracy of above 91% for able-bodied subjects. It is similar to the strategy proposed by Aaron et al who included a few of novel subject's level walking in the training data to create a user-independent classifier, increasing the recognition rate from 48% to 86%[14].This may be explained by the generalization ability of the LDA classifier found in many similar studies[6, 15].

Note that only two able-bodied subjects were recruited for the experiment in the study. It would be investigated in future studies whether the similar results could be observed in more able-bodied subjects and amputees. In additional, more effective solutions will be employed. And in terms of clinical use, a lower dimension of EMG signals would be used in further work.

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