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Reduction of the Effect of Arm Position Variation on Real-time Performance of Motion Classification*

Yanjuan Geng, Fan Zhang, Lin Yang, Yuanting Zhang, *Fellow, IEEE*, and Guanglin Li, *Senior Member, IEEE*

Abstract — **A couple of studies have been conducted with able-bodied subjects and/or arm amputees to investigate the impact of arm position changes in the practical use of a multifunctional myoelectric prosthesis. The classification accuracy calculated offline from electromyography (EMG) recordings was used as a performance metric in these studies, which is not a true measure of real-time control performance. In this study, the influence of arm position changes on the real-time performance of EMG pattern recognition (EMG-PR) control was quantitatively evaluated with four real-time metrics including motion response time, motion completion time, motion completion rate, and dynamic efficiency. Ten able-bodied subjects participated in the study and a cascade classifier built with both EMG and mechanomyogram (MMG) recordings was proposed to reduce the impact of arm position variation. The pilot results showed that arm position changes would substantially affect the real-time performance of EMG pattern-recognition based prosthesis control. Using a cascade classifier could significantly increase the average real-time completion rate (p-value<0.01). This suggests that the proposed cascade classifier may have potential to reduce the influence of arm position variation on the real-time control performance of a prosthesis.**

I. INTRODUCTION

Commercially available upper limb myoelectric prostheses are commonly controlled with the amplitude of EMG signals. Due to the limited functionality and the lack of intuitive control [1-2], current myoelectric prostheses are often discarded by users. In order to improve the control performance of myoelectric prostheses, EMG-PR based prosthetic control approaches have been proposed for a couple of decades and well investigated with many research groups worldwide [3-15]. These studies have showed that EMG-PR based control methods have the potential to allow users for easier and natural control of myoelectric prostheses with multiple degrees of freedom. Most previous efforts concentrated on evaluating the capability of EMG-PR algorithms in classifying a number of motion classes involved in amputated arms in an ideal laboratory setting. Recently, some disparities between a laboratory setting and practical use of a myoelectric prosthesis have also caught much more attentions of the research groups. The effects of some issues that would be inevitably encountered in the clinical setting on control performance of myoelectric prostheses have been investigated [7-9]. For instance, Tkach et al. investigated the effect of EMG signal changes due to recording condition alter such as electrode location shift, muscle contraction variation, and muscle fatigue overtime [7], Simon et al. reported the use of decision-based velocity ramp that could attenuate movement speed after a change in classifier decision [8], and Young et al. investigated how the size of the electrode detection surface and the electrode orientation affect the robustness of EMG pattern recognition based prosthesis control system [9].

Another important disparity between a laboratory setting and a practical setting is the arm position changes. In most of previous investigations, EMG signals recorded in one specific arm position were used to train and then test a motion classifier. Thus the high classification accuracy could be often achieved in this experimental setting. However, when doing a movement in different arm positions from the specific training position, the EMG recording patterns would be changed, resulting in the decrease of motion classification accuracy. Recently, a couple of research groups have conducted the studies with able-bodied subjects and/or arm amputees to evaluate the effects of arm position variation on the classification performance and propose some methods to reduce this kind of effect [10-12]. These findings indicated that the influence of arm position changes on the motion classification performance was significant and some methods could diminish their impact.

As usual, these previous studies used classification accuracy (or error) as a performance metric to assess the influence of arm position variation on prosthetic control performance. It is important to note that the classification accuracy is the ability of a classifier to identify a desired motion class while a subject holds different movements for several seconds. The offline accuracy is calculated by post-processing EMG recordings, not a true measure of real-time control performance of prosthesis. Thus, it remains unclear how the arm position variation affects the control performance of myoelectric prosthetic system in real-time operation. Furthermore, real-time performance metrics are required to examine the clinical robustness and accuracy of pattern recognition control.

In this study, we first investigated the effect of diverse arm positions on the real-time control performance of

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Yanjuan Geng, Fan Zhang, Lin Yang, Yuanting Zhang, and Guanglin Li are with the Key Lab of Health Informatics of Chinese Academy of Sciences (CAS), Shenzhen Institutes of Advanced Technology, CAS, Shenzhen, Guangdong 518055 China (Phone: 86-755-86392219; e-mail: gl.li@)siat.ac.cn.).

Yuanting Zhang is also with Biomedical Engineering at the Chinese University of Hong Kong, Hong Kong, China.

Fan Zhang is also with the School of Computer Science and Technology, Jilin University, Changchun 130012，China.

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multifunctional myoelectric prostheses with ten able-bodied subjects. And then the performance of a two-stage cascade classifier in diminishing the impact of arm position variation would be estimated. Both EMG and mechanomyogram (MMG) signals recorded simultaneously were used as input signals of the cascade classifier to identify a number of arm movements. An experimental protocol was designed to mimic the situation of the real-time control of myoelectric prostheses. Three real-time control performance metrics (motion-selection time, motion-completion time and motion-completion rate) proposed by Li et al. [13-14] were adapted in the study. In addition, a new performance metric called dynamic efficiency was proposed to assess how well the target task was successfully completed by a subject. This study would provide important guide to make myoelectric prosthesis systems be clinically viable.

II. METHODS

A. Participants and Data Acquisition

Ten able-bodied subjects (3 male and 7 female) aged from 22 to 33 participated in the study. The protocol of this study was approved by Shenzhen Institutes of Advanced Technology, Chinese Academy of Science. All subjects gave written informed consent and provided permission for publication of photographs with a scientific and educational purpose.

A commercial wireless biological signal acquisition system (*Delsys Inc, Boston, USA*) was used to acquire EMG data acquisition with four bipolar EMG sensors. Each EMG sensor is integrated with a built-in tri-axial accelerometer, so the EMG and Mechanomyography (MMG) signals could be recorded simultaneously with the hybrid sensors. For each subject, two sensors were placed on the proximal end over the pronator muscle and supinator muscle, and another two were placed on the distal end over the flexor muscle and extensor muscle, respectively. EMG signals were filtered with a band-pass filter (20-450 Hz) and MMG signals were filtered with a low-pass filter (50 Hz). A commercial data acquisition card (*USB-6218, National Instruments Corp.*) was used to convert the analogue signals from Delsys system into digital signals and send them to a computer. The sampling rate of both EMG and MMG signals was 1kHz.

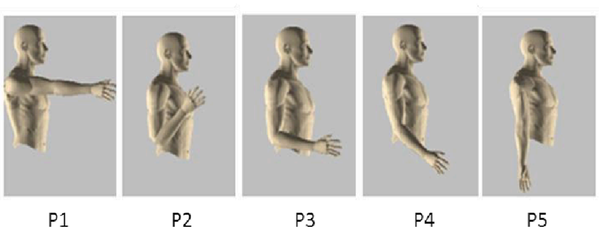

Figure 1. Five arm positions in the sagittal plane

Five arm positions (Fig.1) and seven classes of forearm movements were considered in the study. The seven forearm motion classes were hand open/close (HO/HC), wrist flexion/ extension (WF/WE) and wrist pronation/supination (WP/WS) plus one "no movement (NM)" class. Every subject was asked to follow the prompt image of a movement to perform the seven forearm motion classes in each arm position with a moderate-force muscle contraction. Each movement contraction were sustained for 4s and repeated twice, thus 8s hybrid signals (EMG and MMG) could be recorded for each motion class in an arm position and then used for classifier training and testing.

B. Pattern-Recognition Based Classifiers

Two classifier configurations, single-stage classifier and two-stage cascade classifier, were applied in the study. For each subject, a conventional single-stage classifier was trained with EMG recordings from one specific arm position and used for the identification of the seven movements. A cascade classifier newly proposed by our group was consisted of two sequential classifiers, as shown in Fig. 2. The first stage was trained with MMG recordings as a position classifier to identify the arm positions and the second stage was trained with EMG recordings as a motion classifier to classify the classes of seven movements in an arm position. Each of the five arm positions had a motion classifier, totally five motion classifiers in the second stage.

In the study, four time-domain features (mean absolute value (MAV), number of zeros crossings, number of slope sign changes, and waveform length) for EMG data and three time-domain features (MAV, variation and maximum value) for MMG data were extracted from signal recordings to form a feature matrix. A shifting analysis window with a time length of 150ms and a time increment of 50ms was used in feature exaction. Linear discriminant analysis (LDA) pattern recognition algorithm was used to build the classifiers.

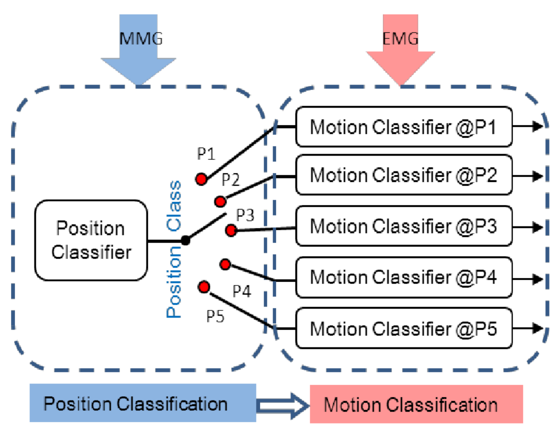

Figure 2. Configuration of the two-stage cascade classifier.

C. Motion-Test Environment and Performance Metrics

A Motion-Test environment (MT) was developed to mimic the situation of the real-time control of myoelectric prostheses with aforementioned classifier configurations. The conventional single-stage classifier was firstly used to evaluate the real-time control performance of multifunctional myoelectric prostheses, and then the two-stage classifier was applied to attenuate the impact of arm position variation, thus all subjects were required to participate in two real-time experiments. With the two-stage cascade classifier in real-time experiment, the position classifier was first used to identify the target arm position for choosing a movement classifier corresponding to the arm position, and then the selected motion classifier was used to recognize the target class of movements.

In either of the two real-time experiments, each subject was required to follow a target motion image and a target arm position image that randomly prompted on computer screen to perform the seven motion classes for three times in each of the five arm positions. Totally, each subject needed to execute 105 movements. A motion trial was considered completed if it was successfully performed through the full range of a motion within 5-second time limit. Dynamic data were recorded and used to quantitatively evaluate the real-time control performance.

Four performance metrics were used to evaluate the real-time performance of proposed classifier configurations, which were the motion response time, motion completion time, motion completion rate, and the dynamic efficiency. The former three metrics were adapted from previous studies [13-14], thus only simple definitions were given herein. The response time was defined as the time from the target movement start to the first time that the subject performed the target movement correctly. The time from the first correct movement identification to motion completion was defined as the completion time. The motion completion rate was the percentage of successfully completed motions out of the total attempted motions (105 target motion tasks in each of two real-time experiments) within the time limit. The dynamic efficiency was used to describe how well the target task was finished, which was defined as the percentage of number of correct decisions (target class) over total number of decisions from the first correct decision to the target task achievement, as shown in Fig. 3. The completion time and dynamic efficiency were only calculated for successful tasks. Paired *t*-test was used to assess the statistic difference between the means of compared data.

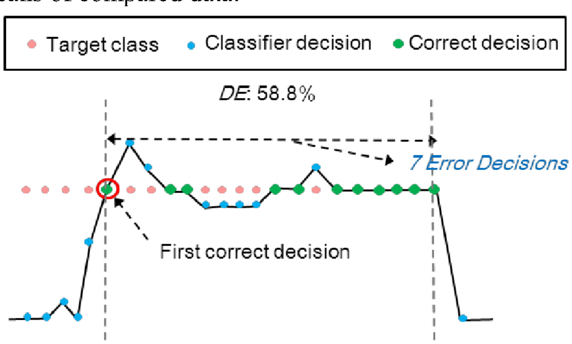

Figure 3. Definition of the Dynamic Efficiency

III. Results

The offline average classification accuracy across all subjects when using single-stage classifier as well as that when using cascade classifier with hybrid signals were around 99.0%, because the position classification accuracy with MMG data had always kept 100% in cascade classifier configuration. Fig. 4 shows the offline motion classification accuracy and motion completion rate from the two classifier configurations for all ten subjects. When using a two-stage cascade classifier in real-time MT analysis, the average completion rate across all subjects was around 90.2%, which was about 4.9% higher than that (85.3%) when using a conventional single-stage classifier (p-value<0.01). It can be seen from Fig. 4 that except subject #6 (AB06), all other subjects could achieve higher motion completion rates with a cascade classifier in comparison to those with a single-stage classifier.

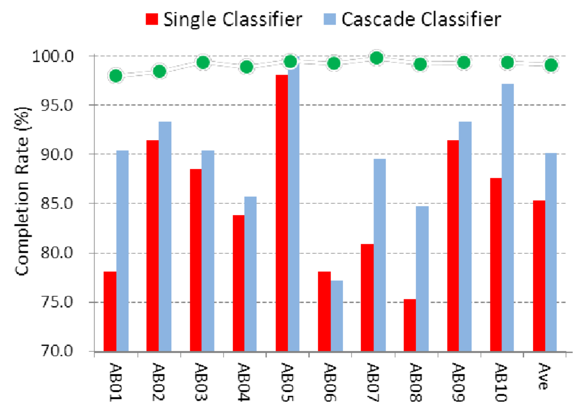

Figure 4. Offline classification accuracies and real-time completion rates when using the two classifier configurations for all ten subjects, respectively. The green solid circles denote the offline classification accuracy.

Table I summarizes three performance metrics from two classifier configurations. The values of Table I were averaged over all the ten subjects. Compared to the conventional single-stage classifier, the cascade classifier had a shorter average response time by 0.06s (p-value=0.02), whereas the completion time and dynamic efficiency were no significant different between the two classifier configurations.

TABLE I. Comparison of Performance Metrics in Two Classifier Schemes

Classifier Scheme	Response Time (s)	Completion Time (s)	Dynamic Efficiency
Single-Stage Classifier	0.92±0.11	1.18±0.11	86.4±4.5%
Cascade Classifier	0.86±0.09	1.18±0.06	87.3±2.9%

Fig. 5 shows the average completion rate over all the ten subjects versus the five arm positions (Fig. 5(a)) and the average completion rate versus the seven motion classes (Fig. 5(b)). When using the cascade classifier, subjects could achieve a higher average completion rate in four of the five motion positions (except in the position P3) than that when using the single-stage classifier (Fig. 5(a)). The maximum difference of motion completion rates between the two classifier configurations was observed in the position P1, with an increase of about 13% when using cascade classifier over the single-stage classifier. In position P3, the two classifier configurations showed a similar completion rate. The average completion rate over all the five arm positions was higher in five of the seven motion classes (Fig. 5(b)) when using the cascade classifier than that with a single-stage classifier. The completion rates increased by approximate 10% for WP, WS and RT. For hand open class, the completion rate with the cascade classifier was about 4% lower than that with the single-stage classifier.

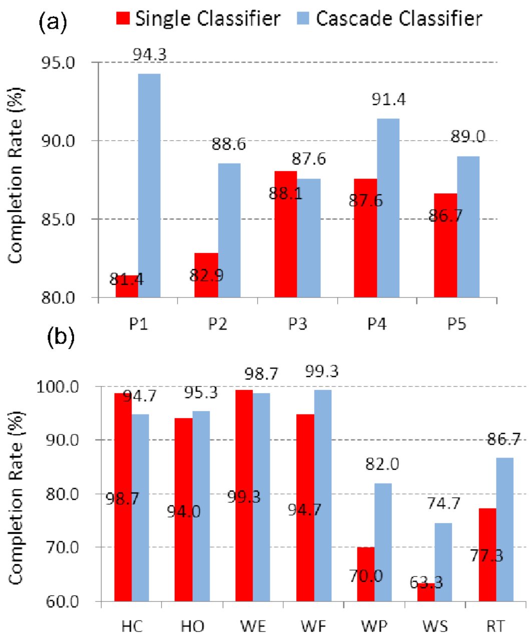

Figure 5. (a) Completion rate vs. arm positions and (b) Completion rate vs. motion classes.

IV. Discussion

With a single-stage classifier trained with four channels of EMG signals, the offline average motion classification accuracy across all the seven arm positions and all the ten participants was around 99.0%. However, the real-time motion completion rate was only 85.3% with the trained EMG classifier (Fig. 4); this indicated that arm position changes would substantially affect the real-time performance of EMG pattern-recognition based prosthesis control. This also revealed a low correlation between offline classification accuracy and real-time performance, which is consistent with a previous study [15]. Therefore, it is necessary to investigate the real-time performance of EMG pattern-recognition based control methods in practical setting before making a myoelectric prosthesis clinically viable.

Using a cascade classifier trained by hybrid EMG and MMG signals to replace the single-stage EMG classifier, the average real-time completion rate over all subjects could be significantly increased. In addition, compared to a conventional classifier configuration, a cascade classifier configuration could achieve similar or a little better real-time performance in response time, completion time, and dynamic efficiency. These suggested that the cascade classifier would be less sensitive to arm position changes than the conventional EMG classifier. Note that generally speaking, a cascade classifier configuration outperformed a conventional EMG classifier configuration. However, a cascade classifier did not work well in all cases. It can be seen from the results showed in Fig. 5 that in some cases, the cascade classifier had similar or lower real-time performance as or than the conventional classifier.

Note that only able-bodied participants were included in this study. Most of them had some previous experience in EMG recording experiments and were familiar with the real-time test environment. Our previous study showed that the amputated arms have less affected by arm position changes than the intact arms [16]. Whether is the finding also true in real-time control of a myoelectric prosthesis? To answer this question, the final users of myoelectric prostheses, arm amputees, will be included in our ongoing works.

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