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Resolving the adverse impact of mobility on myoelectric pattern recognition in upper-limb multifunctional prostheses

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ABSTRACT

Electromyogram pattern recognition (EMG-PR) based control for upper-limb prostheses conventionally focuses on the classification of signals acquired in a controlled laboratory setting. In such a setting, relatively stable and high performances are often reported because subjects could consistently perform muscle contractions corresponding to a targeted limb motion. Meanwhile the clinical implementation of EMG-PR method is characterized by degradations in stability and classification performances due to the disparities between the constrained laboratory setting and clinical use. One of such disparities is the mobility of subject that would cause changes in the EMG signal patterns when eliciting identical limb motions in mobile scenarios. In this study, the effect of mobility on the performance of EMG-PR motion classifier was firstly investigated based on myoelectric and accelerometer signals acquired from six upper-limb amputees across four scenarios. Secondly, three methods were proposed to mitigate such effect on the EMG-PR motion classifier. From the obtained results, an average classification error (CE) of 9.50% (intra-scenario) was achieved when data from the same scenarios were used to train and test the EMG-PR classifier, while the CE increased to 18.48% (inter-scenario) when trained and tested with dataset from different scenarios. This implies that mobility would significantly lead to about 8.98% increase of classification error ($p < 0.05$). By applying the proposed methods, the degradation in classification performance was significantly reduced from 8.98% to 1.86% (Dual-stage sequential method), 3.17% (Hybrid strategy), and 4.64% (Multi-scenario strategy). Hence, the proposed methods may potentially improve the clinical robustness of the currently available multifunctional prostheses.

Trial registration: The study was approved by the ethics committee of *Institutional Review Board of Shenzhen Institutes of Advanced Technology*, and the reference number is **SIAT-IRB-150515-H0077**.

1. Introduction

The conventional upper limb myoelectric prostheses uses amplitude measured at each electrode site to estimate muscle contraction level from which the corresponding limb motion intentions of amputees are decoded and used as control commands [1]. This control method is often characterized by muscle crosstalk, limited dexterity, lack of intuitiveness, and inability to supports multiple degrees of freedom (MDOFs) motions. To intuitively control multifunctional and highly dexterous upper-limb prostheses, a number of previous studies have reiterated pattern recognition (PR) of electromyogram (EMG) as a promising method for decoding the motor intent of amputees [2–4]. Though EMG-PR control method had received considerable research attention, but due to a number of confounding factors, the clinical robustness of the currently available prostheses is not satisfactory thereby limiting their clinical use and acceptance rate [1,5–10].

In recent times, some issues affecting the clinical robustness of EMG-PR based control method for MDOFs prostheses have been studied and reported as follows. Hargrove et al. hypothesized that electrode shift would degrade the performance of EMG-PR based prostheses and

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proposed a method that pools data from shifted electrodes during classifier training [11,12]. Young et al. investigated the effect of electrode size, spacing, and orientation on the robustness of EMG-PR based prostheses [13]. The effect of changes in limb position on the classification performance of EMG-PR based prostheses was also studied, and it was concluded that the inclusion of EMG data from multiple limb positions during training would minimize such effect [14–17]. Furthermore, Scheme and Englehart investigated the impact of variation in force levels during muscle contraction and concluded that such variation would affect the performance of EMG-PR control strategy when applied to prostheses with MDOFs [1]. While these reported progresses have been significant towards the clinical applications of EMG-PR control, there are still some important gaps between the laboratory research results and the clinical performance of multifunctional prostheses that need to be addressed.

Currently in the laboratory domain, EMG data corresponding to different arm movements are often recorded while the subjects maintain a static (seated or standing) position and sometimes with their elbow or arm resting on a chair or table. This experimental protocol often makes it relatively easier for the subjects to produce repeatable muscle contractions across trials when performing certain upper limb motions. Subsequently, a portion of the recorded dataset is used to train a machine learning classifier while the remaining data is fed into the trained classifier to compute the classification accuracy of the limb motions [18]. With this experimental setup, high and consistent classification results are frequently recorded and reported since the training and testing data are acquired while the subjects assumed stationary position that would allow them produce consistent muscle contractions across trials for a specific limb motion. However in clinical practice, amputees are not only expected to use their prosthetic device in static scenarios (sitting or standing) but sometimes in non-static scenarios such as *walking on a flat ground*, *ascending a stair*, or *even descending a stair*.

The following important questions comes to mind: would the classification performance of EMG-PR based prostheses degrade when a classifier is trained with EMG data obtained from a subject in a static scenario and subsequently tested with EMG data acquired while the subject assumes a non-static scenario? If yes, how significant is the impact of variation in scenarios on the performance of EMG-PR motion classifier? How can the impact of variation in scenarios be minimized? What is the effect of change in scenario on individual forearm motion? To answer the first question, the results of our preliminary study showed that variations in scenarios would considerably degrade the classification performance of EMG-PR motion classifier by about 11.35% [19]. It is noteworthy that the results reported in Ref. [19] were obtained from four healthy subjects whose arms are intact. Hence, it remains unclear whether similar results could be achieved with upper limb amputees who are the final users of the prostheses because no work has been done with this population. It is equally important to note that the EMG signal patterns from the residual muscles of an amputated arm may differ from that of the intact arm due to the influence of gravitational force and the number of recruited muscles. Our motivation is based on deep taught towards clinical realization of MDOF prostheses due to observations made on a number of amputees while controlling a virtual prosthesis in the laboratory. Hence, we hypothesized that severe degradation in EMG-PR motion classifier could be subjectively linked to variation in scenarios.

In this study, the effect of mobility on a number of hand and wrist motions across six upper limb amputees was investigated based on myoelectric pattern recognition method. The surface EMG and accelerometer mechanomyography (ACCmmg) signals associated with muscle contractions were recorded from both the amputated and intact arms, and used to decode the limb motion intentions of the amputees. The sensitivity of both types of signals to mobility with respect to limb motion classification was investigated, and three possible solutions for reducing the impact of mobility on limb motion identification were proposed and examined across three different classifiers including linear discriminant analysis (LDA), k-nearest neighbors (kNN), and support vector machine (SVM).

2. Material and methods

2.1. Subjects' information

Six upper-limb amputees consisting of five males and one female participated in the study. Five of the six subjects had transradial amputation and one had a transhumeral amputation. The residual and intact limbs of the subjects were thoroughly examined to ensure proper conformity with the experimental requirement. All the subjects had a unilateral amputation and three of the transradial amputees had experience in the use of myoelectric prostheses. The subjects' demographic information is presented in Table 1.

Before the experiment began, the subjects were clearly briefed about the objective of the study. Thereafter, they all agreed and gave written informed consent as well as permission for the publication of their photographs for scientific and educational purposes. The protocol of this study was approved by the Institutional Review Board of Shenzhen Institutes of Advanced Technology, Chinese Academy of Sciences, China.

2.2. Equipment setup and data collection

The Trigno wireless data acquisition system (Delsys Inc., Boston, USA) was used to record both the surface EMG and ACCmmg signals in the study. A total of six signal sensors were used with each having four silver bar contacts and a built-in 3-axis accelerometer that measures a combination of mechanomyography and arm dynamics. Hence, the six signal sensors provided 6-channels of EMG and 18-channels ACCmmg recordings simultaneously. The device was considered for the data collection due to its ease-of-use, real time feedback on the quality of the recorded signal, and wireless capability, which conform to the requirement of the study.

To acquire myoelectric and accelerometer signals corresponding to various limb motions, the positioning and orientation of the six sensors were preceded by palpation of the residual muscles in the amputated arm in order to identify the length and belly of the muscles as specified in an anatomical atlas [20,21]. By using the Delsys Adhesive Interface, the six wireless sensors were attached to the skin surface underlying the amputated and intact arm muscles of the subjects. And four of the six sensors were placed around the apex of the muscle bulge, 2–3 cm distal to the elbow crease while the remaining two sensors were placed on the flexor and extensor muscles. Before affixing the sensors, the sensor site as well the subject's skin were properly cleaned with alcohol swabs to remove dry dermis and any skin oil that is capable of degrading the quality of the recordings. In situations where a subject's skin is excessively dry, the dry skin cells were dislodged by dabbing the site with medical tapes to ensure proper electrode skin contact. An illustration of the wireless signal sensors placed on the arm of a subject is shown in Fig. 1. Note that similar electrode configuration and skin preparation procedure was applied to the amputated and intact arms of all the amputees to guarantee fair comparison between both arms with respect to effect of mobility on EMG-PR motion classifier.

To investigate the effect of mobility on the classification performance of EMG-PR motion classifier, four different scenarios including sitting on

Table 1
Demographic information of the all participants.

S/ No.	Participants	Residual limb	Intact/Residual limb length (cm)	Amputated since	Height/ Weight (cm/kg)
1	TR1	Left	70/44	9 years	165/65
2	TR2	Right	74/49	10 years	168/50
3	TR3	Left	70/45	<1 year	156/51
4	TR4	Right	68/47	<1 year	163/54
5	TR5	Left	72/43	8 years	162/56
6	TH1	Left	73/25	10 years	166/70

*Note that TR represent transradial amputee while TH denotes transhumeral amputee.