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Quantification and solutions of arm movements effect on sEMG pattern recognition

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ABSTRACT

Robust pattern recognition is critical for myoelectric prosthesis developed in the laboratory to be used in real life. This study focused on the effect of arm movements on surface electromyography (sEMG) pattern recognition for 7 kinds of hand and wrist motions. An experiment was conducted with four static arm conditions and three dynamic arm conditions. Results showed that the arm movements impacted classification performance when the classifier, linear discriminant analysis (LDA), was trained in one arm condition and tested in another arm condition. Inter-condition classification errors (training data and testing data are from different arm conditions) were greater than intra-condition classification errors (training data and testing data are from the same arm condition; average 20.98% vs. 5.26%). Three metrics – repeatability index (RI), mean semi-principal axis (MSA) and mean centroid bias (MCB) – were used to quantify changes in sEMG pattern characteristics of hand and wrist motions. A multi-condition training scheme was explored to improve the robustness of sEMG pattern recognition for hand and wrist motions by reducing the average classification error from 18.73% (LDA trained in single-condition) to 8.20% (LDA trained in multi-condition). Furthermore, a novel classifier, conditional Gaussian mixture model (CGMM) was proposed under this training scheme and yielded a lower classification error than LDA (average 5.92% vs. 8.20%, $p = 0.0078$).

1. Introduction

Surface electromyography (sEMG) has been used for prosthetic device research for over six decades [1]. Control scheme for myoelectric prostheses can generally be categorized into two groups [2]: non-pattern recognition and pattern recognition based. The former group was developed earlier and had been implemented in clinical application. This scheme used the amplitude of sEMG signals from a pair of muscles to control one degree of freedom (DOF) of prehension. If more DOFs were expected, the users needed to perform co-contraction to switch mode. This made the control non-intuitive and cumbersome. So myoelectric prostheses based on this traditional scheme have been typically limited to one or two DOFs [3,4].

It has been proved that the scheme based on pattern recognition might address this limitation and has potential to control multi-functional prostheses [5]. The basic strategy is: when the user performs a natural contraction corresponding to a motion class, a classifier which has been trained is used to recognize the EMG pattern of this contraction, and then the prosthetic hand is activated in an analogous way. This scheme is more intuitive and can control more DOFs movements, therefore, a large number of studies have been carried out to apply this methodology for prosthesis use. These efforts came to fruition by applying many algorithms to extract useful sEMG features (such as time domain features [5,6], time–frequency representation [7,8], nonlinear analysis [9,10] and high order statistics [11]) and design effective classifiers (such as linear discriminant analysis (LDA) [12], artificial neural networks [13,14], Gaussian mixture model [15], heuristic fuzzy logic approach [16] and support vector machine [17]). High recognition accuracy (i.e. above 90%) with classified task containing more than six motion classes has been attained via these algorithms. Furthermore, several studies have carried out real time experiments to examine the possibility of practical application of pattern-recognition-based prostheses (PRBP), often with amputee subjects. In Ref. [18] six channel sEMG signals were applied to direct a physical prosthesis to perform six types of motions and the real-time classification rate was about 85%. In Ref. [19] six channel sEMG

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signals were employed to control a 3-DOF prosthetic virtual prosthesis for accomplishing the target achievement control (TAC) test and the completion rate was about 90%. However, most experiments in these studies were implemented in laboratories under ideal conditions.

Many factors may influence the reliability of PRBP in practical use even though the PRBP demonstrates high recognition rates (above 90%) in the laboratory. One factor is whether the pattern recognition system can maintain satisfactory performance in everyday settings. Many cases could reduce the recognition rate of PRBP such as extended use, the change of load, and arm position change when performing a task. Recently, some research has been conducted to resolve the issue of applying the PRBP in a clinical setting. Tkach et al. [20] studied the stability of time-domain features in three conditions: changing electrode location, variability of muscle contraction effort and muscle fatigue. In their study the most stable feature set could obtain accuracies of 72.6–85.6% for classification of four types of motions. Simon et al. [21] proposed a decision-based velocity ramp for minimizing the effect of misclassification to improve the controllability of PRBP. The completion rate significantly increased from 85% to 95% in a real-time test. Young and Hargrove et al. [22,23] tried to eliminate the influence of the electrode shift by an advanced training strategy, changing inter-electrode distance and electrode configuration. They achieved the improvement of accuracy from 88% to 94% for classifying 9 types of motions.

The limb position effect in myoelectric pattern recognition has been studied by Fougher et al. [24]. They investigated a problem that involved five static arm positions and attempted to solve this problem by combining training data from multi-positions, using accelerometers to record arm positions. Further, Geng et al. [25] extended this work by extending the experiment in transradial amputees, where five static arm positions were considered. These studies gave promising initial results. However, they only discussed some static positions and did not consider dynamic movements when the arm is moving between positions. It is evident that the dynamic movements may bring new problems. In the practical application, the prosthetic hand is controlled in most conditions that the arm is moving. Moreover, lots of previous research [6,15,17,22–24] about myoelectric control was results-oriented. They concentrated on the performance measures without looking into the characteristics of underlying feature space. This may make the explanation of the results insufficient [26] and the methods used less dependable.

Extending our previous work [27], in this paper we try to adopt mathematical tools to quantify the influence of arm movements on sEMG pattern characteristics of hand and wrist motions in the feature space. We conducted an experiment in which the subject performed hand and wrist motions in four static arm conditions and three dynamic conditions with the subject moving his arm in one direction. The arm movements significantly compromised the performance of classification wrist and hand motions. Three metrics – repeatability index (RI), mean semi-principal axis (MSA) and mean centroid bias (MCB) – which were inspired from work in Ref. [28], were adopted to accomplish the quantifying analysis. In addition, two solutions were proposed to alleviate the effect of arm movements on sEMG pattern recognition. The first one, a multi-condition training scheme was explored to improve robustness of sEMG pattern recognition for hand and wrist motions to arm movements. The second one, under the multi-condition training scheme, a novel classifier – conditional Gaussian mixture model (CGMM) – was proposed. The multi-condition CGMM achieved a significantly lower classification error than the multi-condition LDA (average 5.92% vs. 8.20%, $p = 0.0078$).

Fig. 1. Placement of EMG sensors: (a) posterior view; and (b) anterior view. Six wireless sensors were equidistantly placed around circumference of forearm in direction parallel to muscle fiber. Each sensor detected sEMG by a bipolar electrode.

2. Methods

2.1. Declaration

All recruited subjects signed the informed consent before experiment. The procedures conformed with the Declaration of Helsinki.

2.2. Experiment protocol

Six healthy, intact-limbed subjects (one female, five males; right-hand dominant) participated in this study. Before the experiment, the forearm skin was rubbed with alcohol to provide good condition of sEMG signal acquisition. A commercial wireless biological signal acquisition system (DELSYS Inc., USA) was used to record the sEMG signals. As investigated in Farrell's work [29], for sEMG, the targeted and untargeted placement of sensors were not significantly different for classifying hand and wrist motions. Six single differential wireless sensors were placed equidistantly around the apex of the forearm muscle bulge in the direction parallel to the muscle fibers, similar to studies in Refs. [21,24,30,31] (Fig. 1). Signals were band-pass filtered (20–450 Hz) by the hardware of DELSYS acquisition system and sampled at 2 kHz. The collecting system was also used in Ref. [25].

For each trial, the following 7 types of hand and wrist motions were performed in sequential order: hand power grasp, hand open, wrist flexion, wrist extension, hand pinch, hand lateral grasp and rest (Fig. 2). Each motion was held for 5 s with self-evaluated moderate contraction and there was a 5 s break between two adjacent motions. To investigate the effect of arm movements on recognition of these wrist and hand motions, the following seven arm conditions were considered:

S1: the arm was naturally extended toward to ground at the side by facing palm inward (static condition 1, Fig. 3(a)).
S2: the elbow was flexed to 135° in the sagittal plane (static condition 2, Fig. 3(a)).
S3: the upper arm was raised forward on the horizontal plane (static condition 3, Fig. 3(a)).
S4: the upper arm was abducted on the horizontal plane (static condition 4, Fig. 3(a)).
D1: the forearm was swung around the elbow joint between S1 and S2 (2 cycles back and forth in 5 s, dynamic condition 1, Fig. 3(b)).

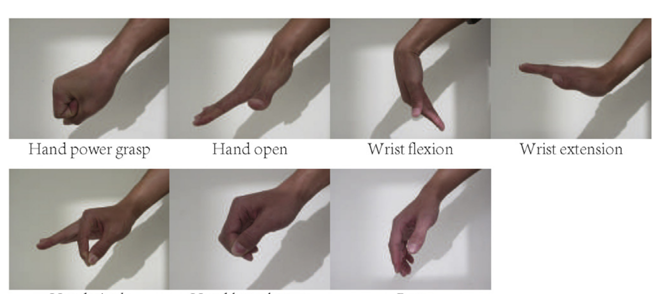

Fig. 2. Seven kinds of motions needed to be recognized.