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Real-time, simultaneous myoelectric control using visual target-based training paradigm

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ABSTRACT

A training strategy for simultaneous and proportional myoelectric control of multiple degrees of freedom (DOFs) is proposed. Ten subjects participated in this work in which wrist flexion–extension, abduction–adduction, and pronation–supination were investigated. Subjects were prompted to elicit contractions corresponding and proportional to the excursion of a moving cursor on a computer screen. Artificial neural networks (ANNs) were used to map the electromyogram (EMG) signals obtained from forearm muscles, to the target cursor displacement. Subsequently, a real-time target acquisition test was conducted during which the users controlled a cursor using muscular contractions to reach targets. The results show that the proposed method provided controllability comparable ($p > 0.1$) with the previously reported *mirrored bilateral training* approach, as measured by *completion rate*, *completion time*, *target overshoot* and *path efficiency*. Unlike the previous approach, however, the proposed strategy requires no force or position sensing equipment and is readily applicable to both unilateral and bilateral amputees.

1. Introduction

Myoelectric control has been used extensively in many applications such as prosthetics [1], robotics [2], and virtual interfaces [3,4]. With this approach, motion intent is estimated from the electromyogram (EMG) signals generated during muscular contractions [5]. Once the user intent has been estimated, it is mapped to a virtual or physical device function using an appropriate control scheme. Myoelectric prostheses typically use *velocity control*, in which the velocity of the device is driven proportional to the intensity of the contraction. Some robot manipulators can provide *position control*, mapping the intensity of effort to a desired position or joint angle of the device [6]. Both *velocity* and *position control* modalities have been used in rehabilitation and training software [8,9].

Different approaches have been employed to estimate the motion intent from the EMG. Commercial prostheses use heuristic methods, in which the EMG amplitude [10] or rate of change [11] from one or two electrodes controls a single degree of freedom (DOF) of the device. If more DOFs are needed, additional “mode switching” logic (using a hardware toggle or muscle co-contraction) is required to select between DOFs, making multi-DOF control unnatural [12]. To overcome this issue, classification based pattern recognition methods have been widely reported in the literature (e.g. [13–17]). These approaches are based on the classification of EMG features measured from multiple electrodes into predefined classes of motion intent. Classification based systems, however, do not inherently incorporate proportional control. Recent work [18] has examined the effect of including proportional control, showing reduced classification accuracy unless training protocols are modified. Moreover, most classification based systems in the literature have not supported the use of combined motions, requiring sequential control. Controlling a prosthesis sequentially is unintuitive and the required motor planning can be burdensome. Recent work [19–22] has investigated the use of classification based systems for simultaneous, but dependent motions control. In [19–22], this was achieved by labeling pre-determined combinations of motions as additional classes. As a result, the classification output was a single class label corresponding to either single or combined motions. The associated intensity of the motions could not be determined independently of each other, and so they were always equal.

In an attempt to provide *independent* simultaneous control of multiple DOFs, recent works have focused on regression based pattern recognition techniques to map the EMG features to a

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continuous variable characterizing motor intent using joint force or position. This approach also inherently incorporates proportional control, providing a continuous intensity estimate in *each* DOF. In the case of robotics, both the EMG and produced force or position are measured from the controlling limb, since the corresponding limb is intact (e.g. [6]). In upper limb prosthetics applications, the force or position cannot be measured directly as the limb is absent, although in some preliminary studies (e.g. [7]) with able-bodied subjects, force or position was measured from the controlling limb. This has motivated the use of a *mirrored bilateral training* strategy, which can be applied to unilateral amputees. With this approach, the force or position is measured from the intact (opposite) limb during bilateral contractions. This technique is supported by evidence that indicates a strong correlation between the motions of the left and right upper limbs during mirrored contractions [23]. Furthermore, a significant correlation between the cortical discharge from the left and right motor areas during mirrored contractions has been reported [23]. Despite a demonstrated reduction in correlation between the intact and affected sides of amputees, *mirrored training* approaches have shown promising results in amputees as well (e.g. [21–23]).

Several works have employed mirrored training for upper limbs using force or position estimation (e.g. [24–34]). This strategy however, is limited to unilateral amputees. For bilateral amputees, Jiang et al. [35] proposed a semi-unsupervised algorithm using non-negative matrix factorization to estimate the wrist joint forces from the forearm EMG. This study focused on offline estimations and three DOFs including wrist flexion–extension, abduction–adduction, and pronation–supination were investigated. The training included single DOF contractions and was used to determine a synergy matrix mapping the EMG amplitudes to force. The results, however, were poor for pronation–supination.

Choi et al. [36,37] proposed a control system using wrist flexion–extension and abduction–adduction. In the training, the users were required to produce contractions according to a cursor on a screen. Subsequently, the cursor traces and corresponding EMG amplitudes were used to determine a non-negative synergy matrix, mapping EMG to motion intent.

In a recent study, Jiang et al. [38] proposed a control scheme based on non-negative matrix factorization using wrist flexion–extension and pronation–supination with able-bodied and amputee subjects. The calibration (training) phase involved four repetitions of full motion range contractions for each DOF using single DOF contractions. A synergy matrix was estimated from the EMG data, using non-negative matrix factorization, to map EMG to motor intent. This algorithm was employed in other studies [39,40], as well.

In this work, a training strategy for simultaneous, independent control is proposed, which addresses important limitations of the mirrored training approach. Unlike mirrored training, this method is applicable to both unilateral and bilateral amputees. Furthermore, it employs visual targets for training, and therefore it does not require force or position sensing equipment. Users are prompted to synchronize their contractions with a moving target cursor on a screen. Artificial neural networks (ANNs) are trained to map the resulting EMG to the corresponding target cursor displacements.

The proposed approach is different from that of [35,38–40] as they did not use visual prompts for training and a synergy matrix was determined from the EMG data by means of blind source separation (non-negative matrix factorization). This work, however, can be considered as an extension of the method proposed by Choi et al. [36,37] which used a visual synchronization training approach. The training protocol involves both single and combined DOF motions, whereas in [36,37], only single DOF contractions were included in the training. Also, ANNs are used for intent estimation from EMG, while a linear estimator was employed in [36,37]. Moreover, wrist pronation–supination is included in addition to the flexion–extension and abduction-adduction motions used in [36,37]. A further contribution of this work is a determination of the efficacy of the proposed training method, as compared to the *mirrored training* approach adopted by other researchers. The same target acquisition test protocol of the authors previous work [31] was employed for control assessment. This analysis allows a direct comparison with previous methods.

Table 1
The wrist and forearm practical contractions used in the protocol.

Index	Contraction
1	Flexion
2	Extension
3	Abduction
4	Adduction
5	Pronation
6	Supination
7	Simultaneous flexion and pronation
8	Simultaneous flexion and supination
9	Simultaneous extension and pronation
10	Simultaneous extension and supination
11	Simultaneous abduction and pronation
12	Simultaneous abduction and supination
13	Simultaneous adduction and pronation
14	Simultaneous adduction and supination

2. Methods

Ten able-bodied subjects (males, ages: 24–39, all right handed) participated in this study. The University of New Brunswick's research ethics board approved the experimental protocol. Three DOFs of wrist flexion–extension, abduction–adduction and forearm pronation–supination were investigated. Eight bipolar wireless surface electrodes (Delsys Inc.) were placed equally spaced around the circumference of the dominant forearm. The electrodes were attached at approximately one-third of the forearm length, measured from the olecranon of ulna. The EMG data were sampled at 1 kHz using a 16 bit A/D converter (NI PCIe-6363). The experiment was performed in a single session and included a training protocol and a real-time target acquisition test, separated by 5 min rest. Fourteen practical contractions listed in Table 1 were included in the protocol. The data acquisition and analysis were performed in Matlab^{TM} (Mathworks, Inc.) with a 3.30 GHz Intel Optiplex 990 workstation. The display adapter was an AMD Radeon HD 6670.

2.1. *Training protocol*

A cursor capable of vertical and horizontal movement and rotation was presented on a computer display, and subjects were prompted to elicit contractions corresponding to the cursor displacement on the screen (Fig. 1). The horizontal, vertical and orientation displacement of the target corresponded to flexion–extension, abduction–adduction, and pronation–supination, respectively. The intensity of contraction was dictated by the amount of cursor displacement in a given direction. The protocol involved fourteen trials associated with the contractions listed in Table 1. Prior to each trial, a picture of the prompted contraction as well as a fixed two dimensional target with orientation was displayed corresponding to the maximum deviation.

The subjects were seated in a standard chair with the dominant (right) elbow comfortably placed on an armrest so that the wrist was not supported by the armrest. To begin each session, the subjects were asked to maintain their wrist in a neutral position with the palm facing inward. Each dynamic movement was 6 s in duration and included 1 s of initial *no motion* during which the cursor