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Enhanced EMG Signal Processing for Simultaneous and Proportional Myoelectric Control

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***Abstract*— A new signal processing scheme is presented for extracting neural control information from the multi-channel surface electromyographic signal (sEMG). The extracted information can be used to proportionally control a multi-degree of freedom (DOF) prosthesis. Four time-domain (TD) features were extracted from the multi-channel sEMG during a series of anisotonic, isometric wrist contractions, which involved simultaneous activations of the three DOF of the wrist. The forces produced at the three wrist DOFs during these contractions were also collected using a customized force sensor. The extracted features and the recorded force signals, as input/target pairs, were then used to train a multilayer perceptron (MLP) neural network. A five-fold cross-validation training/testing method was applied. The resulting performance is a significant improvement over a previously proposed sEMG processing method for the proportional, multi-DOF myoelectric control task.**

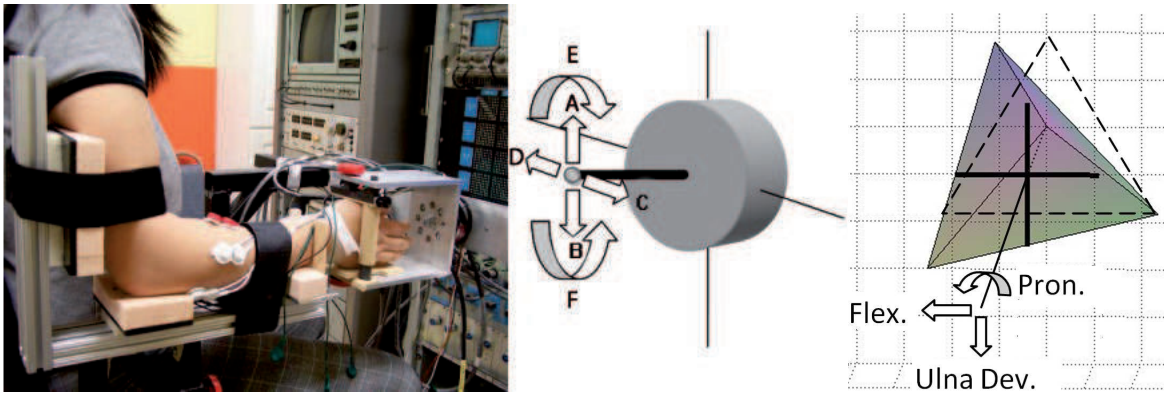
I. INTRODUCTION

Myoelectrically controlled upper limb prostheses have seen significant advances in recent years. Yet, the functionality and intuitiveness of the current myoelectric prosthesis is still very limited. This is due to two main factors. The first one is the paradox between the functionality requirements and signal availability: the higher level of the limb loss, the more functionalities need to be restored, while less information can be obtained from the residual limb. Recently, the revolutionary targeted muscle reinnervation (TMR) procedure greatly addressed this issue [1], [2]. The second factor, which is the main topic of the current study, is that the current signal processing paradigms for sEMG only allows sequential, on/off control. By contrast, the natural neuromuscular control is always a proportional and simultaneous control of multiple DOFs. This disparity makes the current control schemes unintuitive for the prosthetic user, resulting in low clinical acceptance. To address this issue, different approaches are being explored [3]–[6]. In particular, Jiang *et al.* [4] showed that the multi-channel *mean square values* (MSVs) can be modeled as a non-linear mixture of the forces produced at the multiple DOF of a muscular joint, which is termed the *force functions*. Thus, a supervised source separation approach, employing multilayer perceptron network (MLP), was proposed to estimate the *forces functions*. The estimation can be used as the proportional and simultaneous myoelectric control signals. The results presented in [4] and a subsequent study [6] were very promising, particularly for the two DOFs of the wrist: wrist flexion/extension and ulnar/radial deviation. However, when the third DOF, *i.e.* supination/pronation, was activated, the estimation results were not satisfactory. The purpose of the current study is to investigate possibilities of improving the estimation performance of the *force functions*, by using other sEMG features and a different training scheme for the MLP.

II. MATERIALS & METHODS

A. Experimental protocol

The experimental data used in the current study were obtained from the previous study [6]. The experimental protocol is repeated here for the sake of clarity. Twelve able-bodied individuals with no known neuromuscular disorders (seven males, five female; aged from 25 to 50 years) participated in the experiment. Of the 12 subject, 11 were able to finish the experiment protocol, thus the results are only presented using these 11 subjects. These subjects will be referenced as Sub1 - Sub11 in the following. The experimental protocol was approved by the Research Ethics Committee of the University of New Brunswick (REB File #2007-095). During an experiment session, the subject sat in a chair with an armrest on which the right upper arm and forearm of the subject were secured. The right hand of the subject was fixed at a neutral, palm facing inward, position by a custom made handle. The handle was attached to a heavy duty steel frame. A 6-axe force/torque transducer (Gamma FT-130-10, ATI Industry) was mounted between the handle and the steel frame. Eight sEMG electrodes were placed on the arm: seven equally spaced around the forearm, and one on the biceps. The subject was then instructed to perform a series of anisotonic and isometric wrist contractions, at low to medium force levels, during which both forces at the three DOFs (wrist flexion/extension, radial/ulnar deviation, and wrist pronation/supination) and the sEMG were acquired. Two types of contraction sets were performed: single DOF contractions, where only one of the three DOF was intentionally activated; and combined DOF contractions, where two or three DOFs were intentionally activated simultaneously. Each contractions lasted 15 to 30 seconds, and resting periods were provided to avoid fatigue. For further details of these wrist contractions and the data collection procedure, please refer to [6]. The experiment setup is shown in Fig. 1.



(a) Experiment setup (b) The 3D virtualization

Fig. 1. (a) The experiment setup. The force transducer (enlarged illustration on the right) is located between the handle securing the palm and the steel frame. The sensed DOFs are: A/B→ flexion/extension, C/D → radial/ulnar deviation, E/F→ pronation/supination. (b) The 3D visualization of the forces produced by wrist. The broken triangle indicates the resting position of the face of pyramid. The displacement of the pyramid in the figure is due to simultaneous activations of flexion, ulnar deviation and pronation (reproduced from [6] with permission)).

B. Data Processing

1) The generative model of sEMG: Jiang *et al.* proposed a generative model for multi-channel sEMG [6]:

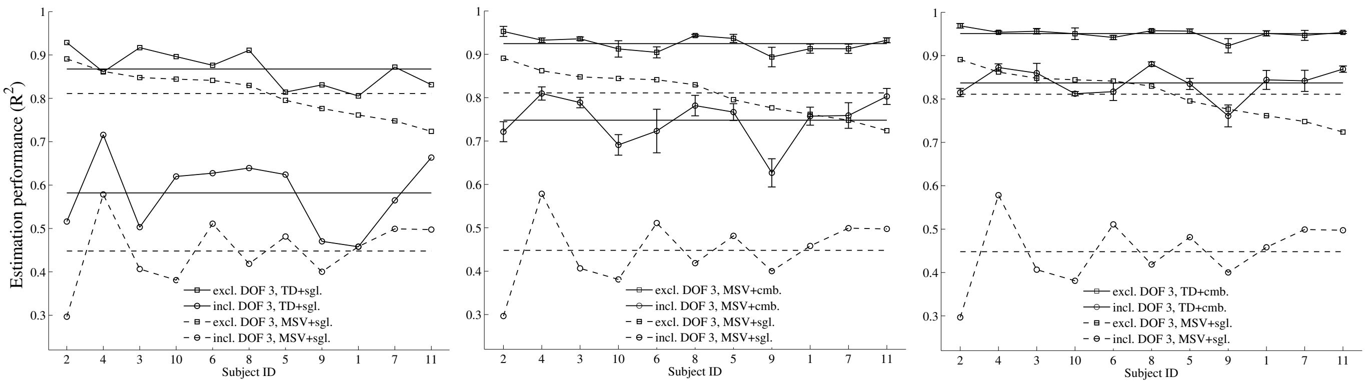
$$\mathbf{Z}(t) = \mathbf{T}[\mathbf{F}(t)] \tag{1}$$

where $\mathbf{Z}(t) = [z_1(t), z_2(t), \ldots, z_L(t)]$ is the MSVs of the observed L-channel sEMG recording from the muscles activating at a muscular joint; $\mathbf{T}[\cdot]$ is an unknown non-linear transformation, determined by the muscular synergy of the activating muscles, the electrical and geometric properties of the muscle tissue and the recording electrodes complex; $\mathbf{F}(t)$ is a set of time varying *force functions*, representing the intended force production, *i.e.* the activation levels at each DOF of the joint. This is the desired multi-DOF proportional control information for myoelectric control application. Unfortunately, only $\mathbf{Z}(t)$ is available. Thus the estimation of the latent $\mathbf{F}(t)$ is a non-linear blind source separation problem, for which there exists an infinite number of solutions [7]. Therefore, *a priori* information regarding the *force functions* must be applied to restrict the space of solutions.

2) Multilayer perceptron estimation: In a study by Jiang *et al.*, the *force functions* produced at the 3 DOFs of the wrist during anisotonic and isometric wrist contractions were estimated using, among other things, a multilayer perceptron (MLP) neural network [6]. In particular, the MSVs of the multi-channel sEMG, $\mathbf{Z}(t)$, were used as the only sEMG-channel feature, and thus the only inputs to the MLP. For the network training phase, the data collected from single DOF contractions (only one DOF was activated) were used: the MSVs of these contractions were the inputs, and the forces produced at the three DOFs were the training targets. After the network was trained, the data collected from combined DOF contractions were used as testing data. The MSVs were the inputs to the network, and the corresponding outputs were the estimation of the *force functions*. A multi-dimensional R^2 index were used to quantify the performance of the estimation, *i.e.* the differences between the measured *force functions*, and the estimation by the network. In general, the MLP estimation performances in the previous study were encouraging, especially when only the first two DOFs were considered. However, the performances significantly degraded when the third DOF, supination/pronation, was activated. In the current study, two new approaches of the MLP training were investigated in order to improve the estimation performances. To evaluate the results of these approaches, one of the methods investigated in [6] (MSV feature and single DOF training of an MLP neural network) was repeated to enable direct comparison.

3) sEMG features: It has been shown that four time-domain features of the sEMG, *i.e.* mean absolute value (MAV), zero-crossings, slope signs changes (turns) and waveform length contain important control information [8]. These time-domain (TD) features are some of the most widely used features for isotonic sEMG in the pattern recognition based myoelectric control algorithms. Therefore, it would be interesting to see if these sEMG features can provide additional control information under anisotonic contractions. In the current study, the TD feature set was extracted from the multi-channel surface EMG using the standard method [8], [9]. Estimation results when using the TD feature set were compared with the results of [6].

4) Training method: In the previous study, the training data only included single DOF contractions. One of main reason of doing so was to validate the mixing hypothesis in [6], consequently to demonstrate the ability of the proposed approach in generalizing from the single DOF contractions to combined DOF contractions. Theoretically, this generalization is only possible for pure linear mixtures. When linearity of the mixture is degraded, so is the generalization ability of the method. Since it was shown that the mixture in (1) is indeed nonlinear, the data from combined DOF contraction may contain additional information regarding nature of the mixing process. Therefore, in the current study, the data from combined DOF contractions were also included in the training data. The data from each contraction were segmented into five segments, and a five-fold cross-validation procedure



(a) Effect of new feature set

(b) Effect of new training method

(c) Effect of both approaches

Fig. 2. **(a)** The effects of the TD feature set. The network training method used to obtain these results is the same as in [6], *i.e.* only single DOF data were used to train the network. The solid lines are the results obtained using the TD feature set, and the dashed lines are the results using the MSV feature (from [6]). The horizontal lines are the corresponding average R^2 index over the 11 subjects for each case. The order of the subjects are ranked by the MSV performance when the third DOF was excluded. **(b)** The effect of proposed training method (only MSV feature is used). The solid lines are the results obtained using combined DOF contractions (denoted cmb. in the legend), and the dashed lines are obtained using only single DOF (denoted sgl. in the legend). The horizontal lines are the corresponding average R^2 index over the 11 subject of each case. Because of the five-fold cross-validation, five R^2 indices were obtained for each subject during the combined training, which is indicated by the vertical bars at the corresponding traces. **(c)** The effect of combining the TD feature set and the proposed training method. The conventions are the same as in plot **(b)**

was carried out. An segment from each contraction was then chosen to form the testing set, and the rest were chosen to form the training set. For each training/test block combination, the MLP was trained 50 times, and the network with the highest R^2 index (discussed in II-C) was retained. This procedure was repeated for each of the five combinations of test/training blocks and mean R^2 and standard deviation (SD) across the five combinations were calculated.

5) MLP structure: It was shown in the previous study that for an eight channel sEMG recording with three DOF of wrist activation, a MLP with one hidden layer consisting of three neurons provided the best estimation performances. The transfer functions of the hidden neurons and the output neurons were hyperbolic tangent sigmoid and linear, respectively. In a preliminary analysis (results not shown), a MLP with the same construct also produced the best performance, regardless of the dimension of the feature set [10]. Thus, the results presented in the current study are obtained using an MLP with this structure.

C. Performance index

The performance index, R^2, in the previous study was also used in the current study. It is a multi-variate index similar to the one used in [11], and is defined as follows:

$$R^2 = 1 - \frac{\sum_{i=1}^{D}\sum_{t=0}^{N}(\widehat{f_i(t)} - f_i(t))^2}{\sum_{i=1}^{D}\sum_{t=0}^{N}(f_i(t) - \overline{f_i(t)})^2} \qquad (2)$$

where D is the number of force functions, N is the number of data samples, $f_i(t)$ is the ith *force function*, $\widehat{f_i(t)}$ is the corresponding force estimate from the MLP, and $\overline{f_i(t)}$ is the temporal average of $f_i(t)$. The numerator in the second term of (2) is the total *mean square error* (MSE) of the estimates and the denominator is the total variance of the *force functions*. The index defined in (2) is a global indicator of the MLP's ability to estimate the *force functions*, since it represents the percentage of total variation of the *force functions* captured by the estimation.

III. RESULTS

For an example of the experiment data, please refer to [6].

A. Effects of additional features

Using the original training method (only single DOF data), when the TD feature set was used the R^2 index was $86.8 \pm 4.3\%$ and $58.2 \pm 8.5\%$, excluding and including the third DOF, respectively. By comparison, when the MSV feature was used, the corresponding R^2 index on the same data was $81.1 \pm 5.3\%$ and $44.8 \pm 7.7\%$, respectively. The TD feature set improved the average estimation performance across all the subjects compared to the MSV feature, particularly when including the third DOF. The results are presented in Fig. 2a.

B. Effects of additional training data

When employing the proposed new training method, *i.e.* using both single DOF data and combined DOF data to train the network, the respective R^2 index was $92.2 \pm 1.9\%$ and $77.1 \pm 5.2\%$, for excluding and including the third DOF. Only the MSV feature was used here, in order to exclude the effect of the TD feature set. The new approach of including combined DOF data in the training set outperformed the training method in the previous study, such that the average performance is significantly increased, and the variability within subjects is reduced. The results are presented in Fig. 2b.

C. Combining the two approaches

When both of the proposed approaches are used, the R^2 index was further increased to $95.1 \pm 1.2\%$ and $83.7 \pm 3.5\%$, for excluding and including the third DOF respectively. This is a significant improvement of the estimation performance of the *force functions*, particularly when the third DOF (supination and pronation) is included. The results of using both approaches are presented in Fig. 2c. In effect, the combined approach indicates that the proposed estimator is able to capture over 80% of the variabilities of the measured force functions for the three wrist DOFs, even when simultaneously activated. Thus, it is possible to provide a rather accurate control signal for proportional and simultaneous control at the wrist joint for trans-radial amputees.

IV. DISCUSSION

The results in the current study demonstrate that both of the proposed approaches provide improved *force function* estimation performance. When comparing with the approach used by Jiang *et al.* [6], the TD feature set alone provides an improvement of 5.7% and 14.4%, respectively for excluding and including the third DOF; when using both the TD feature set and including combined DOF data in the training set, the improvement is increased to 14% and 38.9%, respectively for excluding and including the third DOF. The improvement obtained by introducing the TD feature set indicates that the additional features do contain important neural control information for anisotonic contractions, especially for the third DOF. However, the most significant improvement comes with the inclusion of combined data into the training set, particularly when including the third DOF. The reason for this improvement may be two-fold. Firstly, the muscle synergy among the distal muscles in upper extremities may not be a simple linear mixture at the spinal level, as suggested in the previous study. This is because there are strong evidences supporting significant direct cortical projections to these muscles. Additionally, the nature of these cortical projections is not clearly understood, and may be different between single DOF contractions and combined DOF contractions. Secondly, the experiment setup introduces force translations across the three DOFs, which has been analyzed in the previous study. The translation may vary from contraction to contraction, depending on how the subject is performing the tasks. The results indicates that the mixing process, denoted by $\mathbf{T}[\cdot]$ in (1), may have different characteristics between single DOF contractions and combined DOF contractions. The results in both the current and the previous study by Jiang *et al.* [6] only investigated estimating the force functions using the sEMG together with the measured forces from the wrist of the ipsilateral limb. However, for unilateral upper-limb amputees, the force function targets of the amputated limb is no longer available and this approach is therefore not clinically applicable. In a preliminary analysis (not published), the authors investigated an alternative approach to obtaining the force function targets for the amputated limb, by measuring the forces produced by the contralateral wrist during mirrored bilateral movements for the two upper limbs, albeit only for two wrist DOFs [10]. The results of this analysis is documented in a paper, recently submitted, which shows that the combined approach of this study together with the new bilateral training paradigm provided an estimation performance of $0.92 \pm 0.02\%$ on 10 able-bodied subjects when using forces from the wrist contralateral to the measured sEMG [12]. Additionally the performance was $0.78 \pm 0.04\%$ for one subject with a congenital malformation of the left forearm, indicating that using four TD features and an MLP trained with combined DOF data from the limb contralateral to the amputation, might be a possible solution for unilateral upper-limb amputees.

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