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A Comparison between Force and Position Control Strategies in Myoelectric Prostheses*

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***Abstract*— This work studies the simultaneous and proportional myoelectric force and position estimation of multiple degrees of freedom (DOFs) for unilateral transradial amputees. Two experiments were conducted to compare force and position control paradigms. In the first, a force experiment, subjects performed isometric contractions, while the force applied by the limb and EMG were recorded. In the second, a position experiment, dynamic contractions were permitted during which position of the limb and EMG were measured. Artificial neural networks (ANNs) were trained to estimate force/position from EMG of the contralateral limb during mirrored bilateral contractions. This study involved contractions with combined activations of three DOFs including wrist: flexion/extension, radial/ulnar deviation and forearm supination/pronation. For the given data set, while force estimation demonstrated high accuracy (R^2=0.84±0.02), position estimation performance was relatively poor (R^2=0.57±0.05). Two healthy subjects participated in this work.**

I. INTRODUCTION

Several pattern recognition based systems have been proposed for myoelectric control [1]-[4]. However, the sequential and ON/OFF control nature of pattern recognition systems limits their clinical applicability. To address this issue, simultaneous and proportional control of multiple degrees of freedom (DOFs) has been studied using different controlled variables. To choose the controlled variable(s), we must consider the role of the central nervous system (CNS) in human movements more closely.

Force, length, stiffness, velocity, etc. are some possible answers to the question of "what movements variables are controlled by the CNS?" However, from the available evidence, there does not appear to be a single controlled variable in all movements generated by muscles, and the correct answer to the question above is probably more than one variable. Nevertheless, it is possible that the control of all these variables may emerge from the control of a single underlying variable. But, there is not enough experimental evidence to support such a unified control scheme [5].

There has been a long-standing debate as to whether the human motor system controls kinematics (position) or dynamics (force) related variables. In general, it appears that specific brain regions tend toward dynamics and others toward kinematics, and even within a brain region a neural representation may be altered [6]. In summary, it seems more appropriate that the aggregate discharge of the populations of neurons encodes global rather than single, artificially isolated mechanical variables [7].

Either force or position estimation strategies have been investigated for the simultaneous and proportional myoelectric control of multiple DOFs. Jiang et al. [8] introduced a semi-unsupervised technique to estimate the force in three DOFs including wrist: flexion/extension, radial/ulnar deviation and forearm supination/pronation during isometric contractions. This method did not require the force measurement for training the system. However, the performance was not satisfactory when the third DOF (forearm supination/pronation) was included. To address the case of unilateral amputees, mirrored bilateral contractions have been employed in [9-12].

It has been shown that there exists a significant correlation between the right and left upper limbs forces under bilateral maximal and submaximal contraction. Also, a high correlation between the Movement Related Cortical Potentials (MRCP) recorded from the right and left motor areas during bilateral maximal and submaximal contractions has been reported. The high correlation reflects the interneuronal connectivity between both motor areas linked by common inputs [13].

Nielsen et al. [10] used mirrored bilateral isometric contractions to train an artificial neural network (ANN) using EMG as the input and the force from the contralateral limb as the training target. This approach was applicable to unilateral transradial amputees as it only needed the force measurement from the intact limb. This study, however considered only two DOFs i.e. wrist: flexion/extension, radial/ulnar deviation.

Muceli et al. [11] investigated position control for the same three DOFs using mirrored bilateral dynamic contractions. ANNs were trained using EMG as the input and the position of the contralateral limb as the target. However, the use of dynamic bilateral contractions for both limbs as in [11], [12] is potentially poorly motivated because much of the modulation in EMG with position may be due to change in geometry of the muscle through the excursion of joint angle . In the case of an amputee, the divided muscle or tendon is sutured to the bone or other muscle. Therefore, the change in length of the residual muscles is usually small. An amputee's situation probably more closely resembles a normally limbed individual producing an isometric

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contraction against an immovable load. Even in amputees with muscle that is not tied down, the muscle shortens but not against a load; rather it typically retreats with significant movement. This is not similar to the normal shortening with joint movement in a normally limbed individual.

This paper presents ongoing research to make a comparison between force and position control strategies in simultaneous and proportional myoelectric estimation of multiple DOFs for unilateral transradial amputees.

II. Materials & Methods

A. Experimental Protocol

Two normally limbed healthy subjects (ages: 30, 31) took part in the experiment. The experimental protocol was approved by the University of New Brunswick's Research Ethic board. This study involved three DOFs including wrist: flexion-extension, radial-ulnar deviation and forearm supination-pronation. Seven bipolar wireless surface electrodes (Delsys Inc. [14]) were placed at each arm, six equally spaced around the circumference of the forearm and one on the biceps. The electrodes were attached at a distance from the elbow of almost one-fourth of the elbow-wrist distance. EMG data were sampled at 1000 Hz using a 12 bit A/D converter. Two experiments were conducted to compare force and position control strategies. Electrodes were not detached throughout the experiment to maintain identical electrode locations for both force and position tests.

In the first, a force experiment, subjects sat in a chair with armrests supporting the arms. Two handles attached to a steel frame mounted in front of the chair fixed the hands in a neutral position with palms facing inward. A 6-axis force/torque transducer (Gamma FT-130-10, ATI Industries [15]) was mounted between the right handle and the steel frame, so as the x-axis corresponded to flexion/extension, y-axis to radial/ulnar deviation and z-axis to supination/pronation. Force data were sampled at 1000 Hz using a 12 bit A/D converter. Subjects were asked to perform mirrored bilateral isometric contractions. The same contractions as in [8] were used in this study (two trials of 30 seconds for activation of a single DOF for each DOF and four trials of 15 seconds for each of the combinations of DOFs including 1-2, 1-3, 2-3 and 1-2-3). Subjects were asked to use low to medium force levels throughout the experiment). During the experiment, the measured force was displayed using a rotating 3D pyramid on screen to provide the subject with a visual feedback. EMG from both arms, and force from the right limb were recorded simultaneously. The contractions from both limbs were isometric in this experiment.

In the second, a position experiment, subjects sat in a chair with two armrests holding the arms. Two protocols were followed. In the first, subjects were asked to perform mirrored bilateral dynamic contractions with both limbs free to move. In the second, a handle attached to a steel frame mounted in front of the chair fixed the left hand in a neutral position with the palm facing inward. The subjects were instructed to perform mirrored bilateral contractions with the left limb constrained and right limb free to move. Therefore, the contractions by the left and right limbs were isometric and dynamic, respectively.

Each of the two position experiments consisted of 7 trials including three single DOF activation as well as four free run trials which involved arbitrary combined activation of multiple DOFs. Subjects were asked to use the full range of their movements in each DOF during the experiment. Each trial was 60 s in duration and subjects were allowed to rest between the trials to avoid fatigue. The positions of the markers were captured by a Vicon 512 system [16] using 7 infrared video cameras at 60 Hz. Six reflective ball shaped markers were placed on the right arm as in [11]. To synchronize EMG and position data recordings, the Vicon was triggered through the PC serial port. During this experiment, EMG from both arms, and position from the right limb were recorded concurrently.

B. Data Processing

All data processing was performed offline. EMG data were bandpass filtered (10-470 Hz, eighth order Butterworth filter). It has been shown that time domain (TD) features of EMG including mean absolute value, zero crossings, slope signs changes and waveform length) contain important neural control information [1]. Using a 200 ms window length, TD features of EMG were calculated. Joint angles for the three DOFs were computed from the marker position data as described in [11]. The position data were upsampled to match the time resolution of the EMG. Multilayer perceptron ANNs were used to learn the association between EMG features from each arm and the force (in the first experiment) and position (in the second experiment). All data sets were divided into five blocks (each block containing one fifth of a trial) for a fivefold cross-validation procedure, using one block as the test data and the other four blocks as the training set. The ANNs were trained with the right arm forces/joint angles as targets and EMG features from either the right (ipsilateral) or left (contralateral) arm as inputs to ANNs. The ipsilateral and contralateral arms represented the sound and impaired limbs, respectively. Although it was possible to use a single ANN with three outputs (for three DOFs), a separate ANN for each DOF was employed to achieve possible improvements in the performance. Each ANN had one hidden layer of five neurons, with the hidden and output layers having sigmoid and linear activation functions, respectively. The training algorithm was Levenberg-Marquardt back-propagation. The estimation performance for each DOF was evaluated using the coefficient of determination (R^2). The overall performance for all DOFs was calculated by the multivariate R^2 as proposed in [17].

III. Results

The R^2 values for each DOF and overall performances are listed in Table I for each of the three experiments, i.e. position experiment (both limbs free to move), position experiment (one limb constrained) and the force experiment. Fig. 1 and 2 illustrate the estimated force and position in three DOFs for contralateral limb in subject 1, respectively.

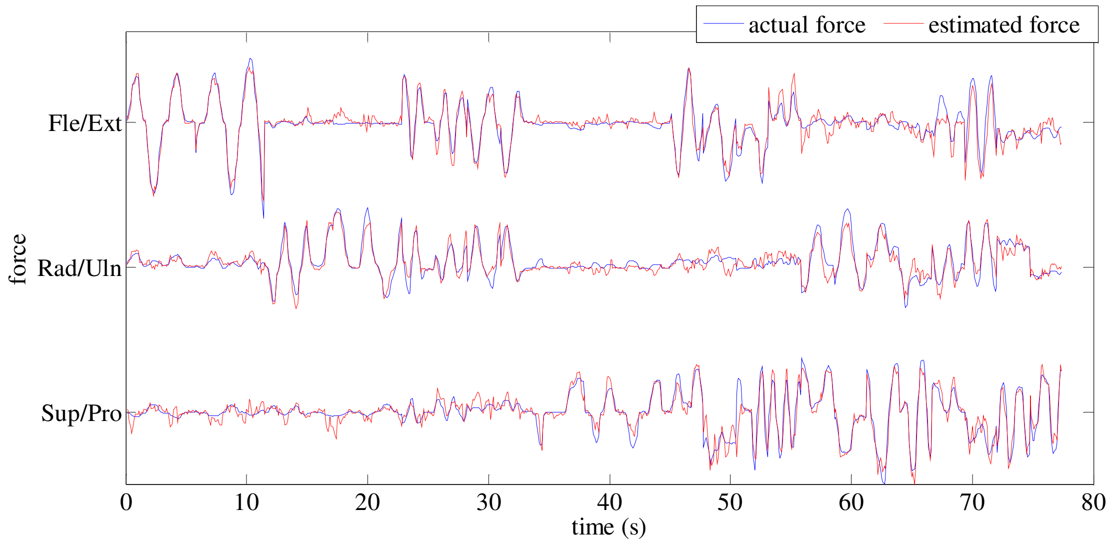

Figure 1. Force experiment: an example of contralateral limb force estimation (low to medium force levels were used).

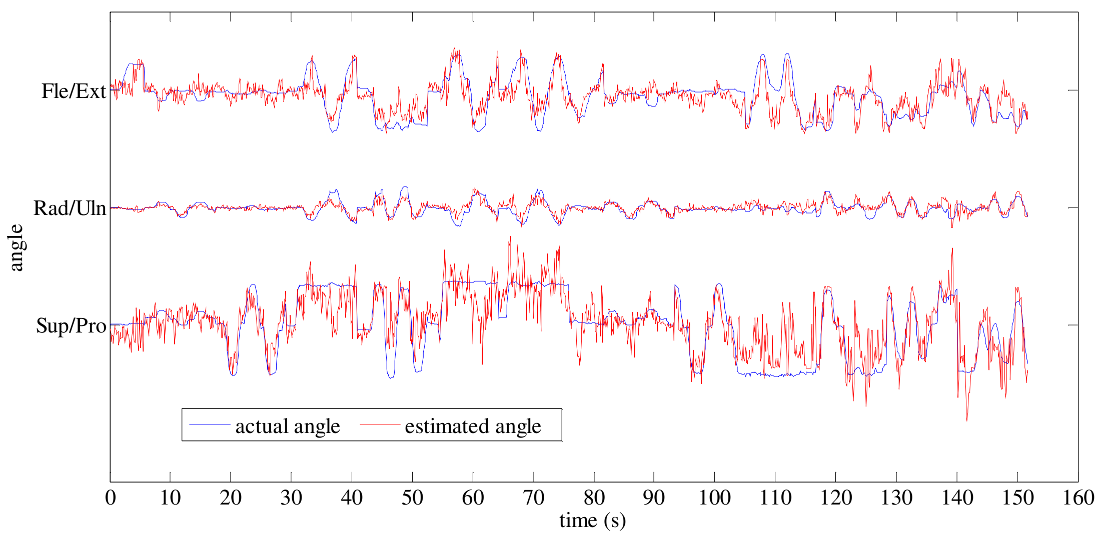

Figure 2. Position experiment (one limb constrained): an example of contralateral limb angle estimation (the full range of movements at each angle was used).

A one-way ANOVA test showed that for the given data set force estimation accuracy was significantly higher ($p=9.9\times10^{-8}$) than position (with one limb constrained).

IV. Discussion

The performance on the ipsilateral limb is consistently better than on the contralateral, which is expected and consistent with previous work [10].

The subjects that participated in this study believed that it was intuitive to perform bilateral contractions when both limbs were either constrained or free. However, it was difficult to do so with one limb constrained and the other free, especially in free run movements.

As mentioned before, EMG varies significantly with changing muscle geometry during joint angle excursion. The difference between the two position experiments in the contralateral case reflects this fact.

The performance of position estimation was poor with respect to force estimation in ipsilateral limb. This may suggest that EMG-position relationship is not as fundamental as EMG-force. In the position experiment, high deviations in estimated angles reflect the low estimation accuracy of ANNs. This shows that similar EMG features might have been associated with very different angles during the training period. This can be clearly seen in the supination/pronation angle estimation.

TABLE I. THE R^2 VALUES FOR CONTRALATERAL (IPSILATERAL) LIMB IN EACH EXPERIMENT

	Position (both limbs free)	Position (one limb fixed)	Force (both limbs fixed)
overall	0.76±0.03 (0.77±0.08)	0.57±0.05 (0.70±0.06)	0.84±0.02 (0.89±0.01)
Fle/Ext	0.85±0.03 (0.88±0.02)	0.60±0.10 (0.84±0.04)	0.86±0.06 (0.93±0.02)
Rad/Uln	0.72±0.05 (0.78±0.04)	0.62±0.08 (0.77±0.04)	0.83±0.03 (0.87±0.02)
Sup/Pro	0.65±0.17 (0.66±0.17)	0.54±0.06 (0.60±0.10)	0.81±0.07 (0.86±0.02)

This poor performance of position estimation can be related to low EMG levels. Since movements in position experiment did not involve pushing against a resistance, the level of effort and EMG was low especially for smaller angles. This made difficulties for ANNs to discriminate between angles. Thus, in order for EMG-position mapping to perform well, it requires a force component.

The movements of muscles under the skin during contractions especially rotation, reduced either force or position estimation accuracies. This movement was more pronounced during dynamic contractions.

The result of the force experiment in the ipsilateral case is similar to the previous work [9]. Nevertheless, mirrored bilateral contractions were not employed in [9]. The performance of the position experiment (both limbs free) is comparable to the results reported in [11] for the first two DOFs, but lower by about 10% for the supination/pronation angle. However in [11], high density EMG was employed and the contractions were limited to the prescribed movements, and did not include a free run off contractions, as used here.

V. CONCLUSION

The purpose of this paper was to compare force and position myoelectric control strategies for unilateral transradial amputees. For the given data set, force control demonstrated significantly higher estimation accuracy compared to position control. The future studies will involve multiple subjects including normally limbed and amputee individuals.

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