FORCE ESTIMATION IN MULTIPLE DEGREES OF FREEDOM FROM INTRAMUSCULAR EMG VIA MUSCLE SYNERGIES

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ABSTRACT

Force estimation is an important factor in proportional control of prosthetic arms. Muscle synergies seem to be relevant for force estimation since they are patterns of co-activations of muscles during actions. This study investigates the use of muscle synergies extracted from intramuscular electromyography (EMG) for estimating force during multiple degrees of freedom (DOF) voluntary contraction. For this purpose, muscle synergies of the contractions were extracted from six superficial forearm muscles from four able-bodied subjects. Also, the isometric force produced by the wrist during these contractions were recorded along multiple axes each responsible for one DOF. The neural inputs were then fed to an Artificial Neural Network (ANN) to estimate the force. The results show a significant correlation between the estimated and measured force.

INTRODUCTION

Prostheses can play an important role in improving the quality of life of amputees. One way to increase the functionality of prosthesis is to provide an effective control of the velocity and applied force (proportional control). One important factor in proportional control of prosthesis is to estimate the level of activities produced by the user performing the tasks [1].

On the other hand, redundancy in the neuromotor system potentially allows for multiple modalities of muscle coordination to produce sub-maximal forces for different tasks [2]. Hence, the relative proportions of muscle activations could potentially change with different conditions of force level during a movement. One major viewpoint concerning the paradigm that the neuromotor system uses for muscle coordination to accomplish control of forces is based on the modularity of motor control. This viewpoint hypothesizes predetermined patterns of co-activations of muscles, i.e. muscle synergies, during performing a task as the primitive modules of muscle coordination [3]. Regarding muscle synergies, this unit of motor output has been referred as consisting of the coupled activation of a group of muscles. Muscle synergies hypothesis suggests that intending to move is just activating the corresponding muscle synergies that turn on the muscles necessary to accomplish the movement.

This report discusses how muscle synergies may have the potential for providing effective proportional force control. We investigated this through examining the consistency of the muscle synergies involved in producing four different wrist movements (flexion, extension, abduction, and adduction) and their combinations and studied their power in estimating the produced force. The objectives of this experiment are to collect intramuscular EMG along with the produced force from some subjects while performing some tasks. From these data, the muscle synergies and the neural inputs will be extracted. These estimated neural inputs correspond to the estimated forces in each DOF.

METHODOLOGY

<u>Data collection protocol</u>

Our experimental protocol was approved by the University of New Brunswick's Research Ethics Board. The data were collected from six superficial muscles (FCU, PL, FCR, ECR, EDC, ECU) from four normally limbed subjects (one female and three males within the age range 23 to 50). Muscles were located using an ultrasound device and the electrodes (custom-made by use of hypodermic needles and Teflon coated wires (A-M Systems, Carlsberg, WA; diameter 50 μm)) were at depth of approximately 1 cm below the fascia. Subjects were required to perform different movements associated with 2 DOF of the wrist including extension, flexion, abduction, adduction, and combinations of them. Subjects exerted force while seated in a chair with their right arm placed in an armrest. A custom-made hand support incorporating a commercially available dynamometer (Gamma FT-130-10, ATI Industries) was used to provide feedback to the subjects about the level of activation for each task.

Specialized MATLAB-based acquisition software was used to guide subjects through a data acquisition session. Each session consisted of two trials of multiple repetitions of each motion. Subjects were prompted to complete medium force isometric contractions followed by a 2 minute rest period between trials.

The intra-muscular EMG signals were amplified with a gain of 1000, bandpass filtered between 0.1 – 4.4 KHz and A/D sampled with 12 bits resolution.

Extracting muscle synergies

According to muscle synergies hypothesis, any given muscle response should be describable as the linear combination of a small number of muscle activation patterns or muscle synergies [4]. Further, both the elements of the synergies and their weighting within each response should be positive, because muscle activations are being considered. Tresch et al. [4] proposed that muscle synergy hypothesis can be formalized in the following model:

$$v_j^{obj} = \sum_{i=1}^{N} h_{ij} w_i \qquad h_{ij}, w_i \geq 0 \tag{1}$$

which is the jth observed pattern of muscle activations. In the model above h_{ij} is the neural input or the positive weighting coefficient of the ith muscle synergy for the jth response, w_i is the ith muscle synergy and N is the number of muscle synergies. The full model written in matrix form is:

$$V_{m\times o} = W_{m\times n} \times H_{n\times o} \tag{2}$$

where V is the m × o (m muscles, o observations) recorded EMG data matrix, W is the m × n (n synergies, m > n) column-wise matrix of synergies and H is the n × o matrix of time-varying neural inputs. V is given, and W and H are to be determined.

Identification of muscle synergies can be done through different methods such as Principal Component Analysis (PCA), Maximum likelihood factor analysis (FA), Nonnegative matrix factorization (NMF), and Independent Component Analysis (ICA). NMF is the most common method used to identify muscle synergies and their activation coefficients underlying a set of muscle activation patterns [5], not only because the synergy components discerned by NMF likely have more physiological relevance due to the restriction of non-negativity [6], but also because it does not restrict the discerned synergies to be orthogonal or statistically independent, as do PCA and ICA respectively [7].

Identifying the number of synergies

We found the smallest number of components necessary to explain at least 90% of the variance in each subject using NMF. Figure 1 shows how this explained variance grows by increasing the number of synergies for a typical subject.

Force estimation

Extracted neural inputs are fed to an ANN (with two hidden layers and 10 neurons). The target of the ANN is the measured force in each DOF during training; with novel EMG data the output is an estimate of produced force. For 2-DOF tasks, the training data was extracted from the signal recorded during performing combined tasks. The ANN was trained for each subject separately. Since the recording trials included multiple repetitions of each movement, each trial was divided into two segments and the ANN was trained by the first 60% of the data from each segment and tested with the rest of the data from that segment.

The network training stopped when either the validation error was growing for six sequential epochs or the error went below a predefined threshold (0.001). In order to evaluate our estimation results, Mean Absolute Values (MAV) of the same data (of all the channels) were used to estimate the associated force.

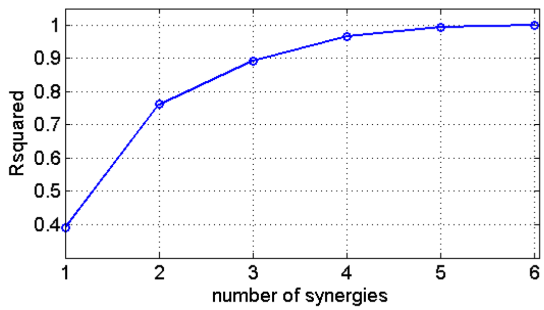

Figure 1: The change in the described variance by increasing the number of synergies (axes are unitless)

RESULTS

Figure 2 shows three muscle synergies and their corresponding neural inputs extracted from a sample segment of intramuscular data including a number of wrist flexions and extensions (shown by *F* and *E* respectively).

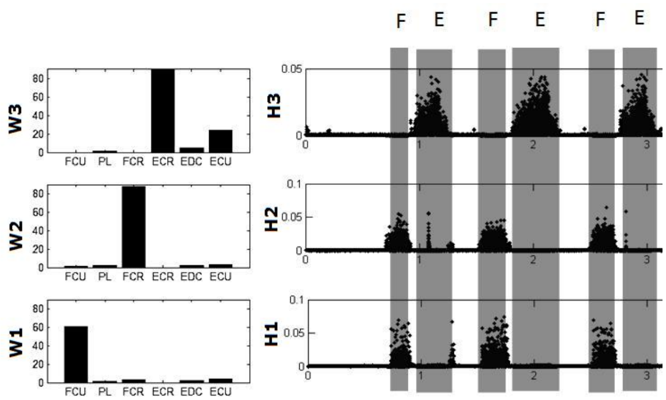

Figure 2: Example of extracted synergies and their coefficients. Dark shades on the neural inputs shows the associated movement (*E* for extension and *F* for flexion)

As Figure 2 shows, each synergy indicates a pattern of activities of six muscles and has a dominant active muscle making the synergies sparse. Also the relation between the synergies and the static force of each DOF can be observed in Figure 2. Activation of the flexors is mainly reflected by the second and the third synergy whose coefficients increase during the flexion part of the data. On the other hand, the first synergy is mainly characterized by the extensors and a considerable increase is observed in the first coefficient during extension.

In our experiment, we extracted a sufficient number of synergies to describe at least 90% of the variance of the recorded data. For all the subjects and for all the trials only a few numbers of synergies (two or three) were enough to describe that much of the variance. In order to keep them within the bandwidth of the measured force, the estimated neural inputs were low pass filtered at 2Hz before being provided to the ANN.

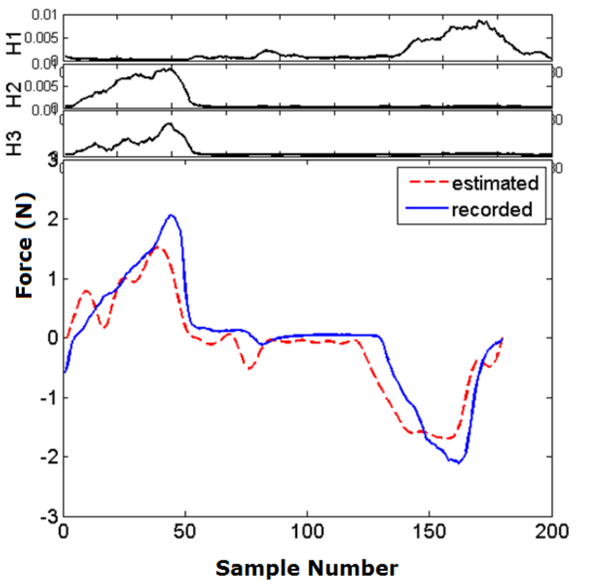

Figure 3: An example of three neural inputs (top plots) along with the recorded forces and the estimation result (bottom plot)

Figure 3 shows the result of force estimation using three neural inputs for a sample segment of data including extension and flexion performed by a subject.

Table 1: Force estimation results via neural inputs and MAV

Task (DOF)	**Input**	**Correlation Coefficients**	**R2**
Flexion/ Extension	Neural inputs	0.9138	0.8168
Abduction/ Adduction	Neural inputs	0.8793	0.7752

Flexion/Extension + Abduction/Adduction	Neural inputs	0.9398	0.7924
Flexion/ Extension	MAV	0.9313	0.8406
Abduction/ Adduction	MAV	0.9025	0.8061
Flexion/Extension + Abduction/Adduction	MAV	0. 9282	0.7665

For all four subjects, the coefficient of determination (R^2) values of the estimation and the correlation coefficients between the recorded force and the estimated values were computed and averaged to evaluate the accuracy of the estimation. First three rows of Table 1 show the results for estimating the produced force in each DOF separately using the neural inputs.

As Table 1 shows, the estimation results are highly correlated with the recorded force and R^2 values indicate acceptable accuracy in the estimation considering the fact that only one feature of EMG signal is being used for estimating force. Most of the estimation error, as one can see in Figure 3, can be the result of scaling and/or delay in estimation with respect to the target and can be accommodated to reduce the error. Thus, the results can still reflect the major behaviors of the target.

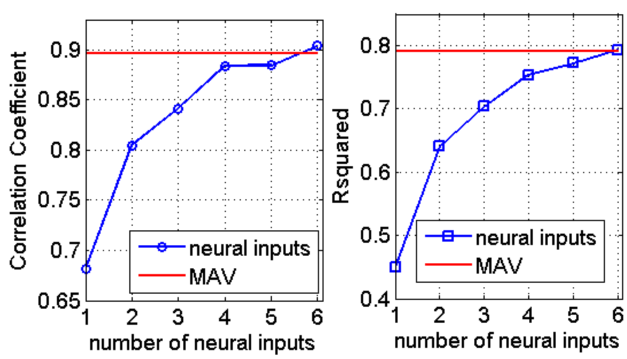

Figure 4: changes in Correlation coefficients and R^2 by increasing the numbers of neural inputs for a typical subject, also compared with result of using MAV as input (axes are unitless)

It is also relevant to further evaluate the achieved results by comparing them with results of estimation via another type of input. In order to facilitate this comparison, we used the MAV of the same data (for all the channels) to estimate the associated force and we showed it in the last three rows of Table 1. When using MAV as input, the accuracy of the estimation is slightly more than using only two or three neural inputs. However, as Figure 4 shows, increasing the number of extracted neural inputs can improve the accuracy of the estimation and sometimes even gets ahead of MAV estimation.

DISCUSSION

The R^2 values of the estimation along with high correlation between the estimated and the target values show that neural inputs are able to estimate the force values with an acceptable accuracy which can get ahead of estimation by MAV in multi-DOF force estimation.

Furthermore, the numbers of neural inputs enough for estimating the force are usually few, i.e. much less than the number of muscles involved in the movement. Thus, using neural inputs not also keeps the estimation in an acceptable accuracy but also reduces the dimension of the estimation model.

Robustness, reduction in the problem dimension, and their ability to accurately estimate the force values make muscle synergies potentially appropriate approach toward the proportional control of prosthesis.

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