Toward Proportional Control of Myoelectric Prostheses with Muscle Synergies

Bahareh Atoufi[1,*]   Ernest Nlandu Kamavuako[2]   Bernard Hudgins[1]   Kevin Englehart[1]

[1]*Institute of Biomedical Engineering, University of New Brunswick, Fredericton NB, E3B 5A3, Canada*
[2]*Center for Sensory-Motor Interaction, Department of Health Science and Technology, Aalborg University, Aalborg, Denmark*

Abstract

Force estimation based on electromyography (EMG) has been proven to be useful for deriving proportional control for myoelectric devices. Muscle synergies seem to be relevant for force estimation since they are patterns of co-activation of muscles during actions. This study investigates the use of muscle synergies extracted from targeted surface EMG for estimating force during multiple-degree-of-freedom (DoF) contractions involving the wrist and hand. For this purpose, muscle synergies were extracted from twelve forearm muscles from eight able-bodied subjects. The constrained isotonic force produced by the wrist and the hand during these contractions was recorded along multiple axes, each responsible for one DoF. The derived neural inputs were then input into an artificial neural network (ANN) to estimate the force. The results were evaluated by comparing them with those obtained using mean absolute values (MAVs) for force estimation. The results obtained using muscle synergies were significantly better ($p < 0.05$) than those obtained using MAVs in the estimation of force when training with both 1- and 2-DoF contractions ($p = 0.02$) and also when training with only 1-DoF contractions ($p = 0.001$). The latter case was important, as a training protocol that includes all desired 2-DoF contractions is very difficult for amputee users. For this case, the results obtained using muscle synergies were significantly improved compared to those obtained using MAVs. In addition, the robustness of muscle synergies was examined across different force levels. The results indicate that muscle synergies are robust and reliable for the force estimation of multiple-DoF tasks, and are thus a promising approach for the proportional control of prostheses.

Keywords: Electromyography (EMG), Artificial neural network (ANN), Muscle synergies, Proportional control, Myoelectric prostheses

1. Introduction

The design and control of dexterous upper limb prostheses is a very challenging task. Despite many breakthroughs over the last several years [1-4], there is still a considerable gap between human hands and artificial hands in the efficacy of imparting control [5,6]. Current electromyography (EMG) signal processing solutions for decoding a user's intended movement are still unable to provide intuitive and reliable proportional force control for amputees. In fact, it is quite common for upper limb amputees to reject the use of their prostheses because of low functionality, among other reasons [7-9]. One important factor in the proportional control of prostheses is to estimate the level of muscle activity produced by the user performing a task [10-12]. For example, accurate grip force control is essential in performing activities such as the grasping of fragile objects, resistance to external forces (e.g., holding a spoon to resist gravity), and applying movement to an object (e.g., turning a knob) [13].

One major viewpoint concerning the paradigm that the neuromotor system uses for muscle coordination to accomplish movement is based on the modularity of motor control [14-16]. This viewpoint hypothesizes predetermined patterns of the co-activation of muscles, i.e., muscle synergies, during task performance as the primitive modules of muscle coordination [17]. These muscle synergies imply a coupled activation of a group of muscles. Redundancy in the neuromotor system potentially allows for multiple modalities of muscle coordination to produce sub-maximal forces for different tasks [18]. Hence, the relative proportions of muscle activations could potentially change with the conditions of force level during a movement.

The scaling of muscle synergies is a necessary property of the neuromotor synergy hypothesis [19]. The muscles within a synergy should maintain the same relative activation levels, and the synergies involved within a task should remain consistent with an increase in the task's force requirements. The scalability

* Corresponding author: Bahareh Atoufi
  Tel: +506-453-4966; Fax: +506-453-4827
  E-mail: bahareh.atoufi@unb.ca

of inputs in myoelectric control paradigms is important because it allows for the implementation of proportional control, i.e., the speed of the motors of the controlled device is directionally proportional to the magnitude of the input signal. The activation levels of muscles embedded in synergies in addition to the activation levels (weights) of synergies can be considered a mechanism for proportional control. If it can be shown that their generality exists within a wide range of produced force, proportional control might be accomplished more accurately in a control space of a lower dimension via synergies. In spite of the interesting attributes of muscle synergies, little research has been performed toward using these modules to control prosthetic hands. Only two major studies [20,21] have examined the concept of muscle synergies as a dimensionality reduction paradigm for the production of a wide variety of human hand postures.

The study by Weis and Flanders [20] described the hand postures associated with the ASL alphabet and with the grasping of everyday objects with a low-dimensional set of muscle synergies, and to align these muscle synergies with postural synergies of the hand. While informative, this study failed to make a compelling case that the new framework established by their extracted synergies was useful within a physiological control paradigm. The efficacy of this framework in predicting new hand postures, which speaks to its robustness and generalizability, is a testable and necessary hypothesis given the accepted definition of muscle synergies [19]. However, this was not explored in their work. In short, the work of Weiss and Flanders only established that muscle synergies can form a descriptive framework for a wide variety of known hand postures.

Ajiboye and Weir determined that muscle synergies form a robust lower-dimensional framework for the prediction of the EMG patterns of new static hand postures. They also performed another investigation that characterized, through a virtual target reaching task, the volitional independence and simultaneous control of multiple degrees of freedom (DoFs) using muscle synergies versus single-muscle inputs [21]. However, their results were based on four muscle synergies that they defined as the best synergies. As mentioned in [21], examining more complex tasks with a higher number of synergies may indicate the superiority of utilizing the synergy paradigm over the individual muscle paradigm. Their results showed that the dominant synergies involved in cylindrical and lateral force-tracking tasks linearly scale with grasp force. Nevertheless, none of these studies examined the power of muscle synergies in estimating the produced force.

The present study primarily investigates the capability of muscle synergies to provide effective proportional force control by extracting synergies with their associated positive weighting coefficients (neural inputs) from recorded muscular activities from 12 muscles during various wrist/hand motions. It is hypothesized that, through muscle synergies, prosthetic devices may be controlled more naturally and in a physiologically expected manner. This study also quantifies the robustness and repeatability of the muscle synergies that are involved in producing various wrist/hand movements across various

exerted force levels. For this purpose, an artificial neural network (ANN) estimator was trained by mapping the neural inputs extracted from a set of motions to a recorded force. The force estimator was then evaluated at force levels that were different from those of the training set, and with multiple-DoF motions that were combinations of the trained motions.

2. Materials and methods

2.1 Data collection

The experimental protocol was approved by the University of New Brunswick's Research Ethics Board. Eight normally limbed subjects participated, one female and seven males within an age range of 23 to 53 years, all right-handed (referred to as Sub1-Sub8). Subjects had no history of neuromuscular disorders.

Surface EMG (sEMG) data were collected from 12 superficial muscles (flexor carpi ulnaris (FCU), palmaris longus (PL), flexor carpi radialis (FCR), extensor carpi radialis (ECR), extensor digitorum communis (EDC), extensor carpi ulnaris (ECU), and biceps) and five intermediate and deep muscles at the site where they are accessible (flexor digitorum superficialis (FDS), flexor policis longus (FPL), pronator teres (PT), flexor digitorum profundus (FDP), and brachioradialis (BR)). Muscles were identified and the EMG electrodes (bipolar silver/silver chloride, Doutrode, Myotronics, Inc., 5870 S. 194th Street, Kent, WA 98032, USA) were placed on the belly of each muscle. A reference electrode was placed on top of the lateral epicondyle. sEMG signals were amplified with a gain of 5000, bandpass-filtered between 10-500 Hz and analog/digital sampled with 12-bit resolution.

Subjects were required to perform different constrained isotonic movements associated with two DoFs of the wrist, including extension, flexion, pronation, and supination, as well as four DoFs of the hand, including power, pinch, key, and spherical grasps. Combinations of the wrist and hand motions were performed as well. 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 record and provide feedback to the subjects about the level of wrist activation for each task. Grasp force was estimated by measuring the fingertip forces, as successfully employed by others [22]. To perform the grasping tasks, four different objects, each associated with one grasp type, were chosen for the subjects to hold. These objects were equipped with force-sensitive resistor (FSR) sensors (custom-made, 1 cm × 1 cm) on their surface to measure the force applied by the fingertips. All signals were sampled at a rate of 1000 samples per second.

2.2 Experimental procedure

The maximum voluntary contraction (MVC) for each subject was recorded to normalize the force levels required during the experiment. MATLAB-based software was used to guide subjects through a data acquisition session. Each experimental session consisted of 96 trials, each of which

contained two repetitions of a 1- or 2-DoF task. Subjects were prompted to complete four low (25% MVC) and four medium (50% MVC) force contractions of each task followed by a five-minute rest period between each set of twelve trials. Each task took roughly six seconds; the exact duration was dependent on the subject's preference.

2.3 Extracting muscle synergies

According to the muscle synergy hypothesis, any given muscle response should be describable as the linear combination of a small number of muscle activation patterns or muscle synergies [23]. 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*. [23] proposed the following model for the muscle synergy hypothesis:

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

for the jth observed pattern of muscle activations. In the model, 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 $m \times o$ (m muscles, o observations) recorded EMG data matrix, W is the $m \times n$ (n synergies, $m > n$) column-wise matrix of synergies, and H is the $n \times o$ matrix of time-varying neural inputs. V is given, and W and H are to be determined. Equation (2) indicates that every matrix of EMG observation can be decomposed into a synergy matrix and its correspondent coefficient matrix. During training, V is the entire training set, used to compose the W synergy matrix. During classification of the test set, V is a 200-ms analysis window, projected onto a novel H matrix using the W matrix.

Identification of muscle synergies can be done through methods such as principal components analysis (PCA), maximum likelihood factor analysis (FA), non-negative 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 [24], not only because the synergy components discerned by NMF likely have more physiological relevance due to the restriction of non-negativity [25], but also because it does not restrict the discerned synergies to be orthogonal or statistically independent, as do PCA and ICA, respectively [26].

The appropriate number of synergies was determined as the smallest number of components necessary to explain at least 90% of the variance of the recorded sEMG for each subject using NMF. Figure 1 shows how this explained variance grows by increasing the number of synergies for a typical subject. For all the subjects, six or seven synergies were sufficient to describe 90% of the variance. In order to keep them within the bandwidth of the measured force, the estimated neural inputs were lowpass-filtered at 2 Hz before being input into the force estimator model.
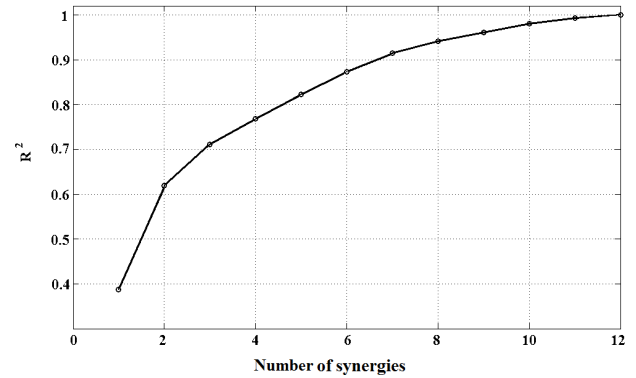

Figure 1. Change in described variance with number of synergies (axes are unitless).

2.4 Data analysis

After the synergies were extracted, the associated neural inputs were input into an ANN. The target of the ANN was the measured force in each DoF during training. With novel EMG data, the output is an estimate of produced force. The ANNs were trained using the backpropagation (Levenberg-Marquardt) algorithm.

The 50% MVC data were used to develop training and validation sets in order to find the optimal structure for the ANN. The validation set was used to determine the optimum number of hidden-layer neurons (eight), and to determine a stopping criterion for ANN training (when either the validation error increased for six sequential epochs or the error went below a predefined threshold of 0.001).

Data were segmented using 200-ms windows with a 50-ms increment. The ANN was trained 50 times and the ANN with the lowest error on the validation data was used for testing in order to estimate the 25% MVC data.

The test analysis was performed on analysis windows of 200 ms in duration. The processing delay for this 200-ms analysis window is minimal (less than 10 ms). It is generally accepted that for a real-time application of the prostheses, the response time should not exceed 300 ms.

2.4.1 Force estimation

The low-contraction profiles (25% MVC) were used for testing and the medium-contraction profiles (50% MVC) were used for training and validating the force estimator model. Of the medium contraction data (training set), 85% (randomly chosen) were used during training and the remaining 15% were used for validation. The training set consisted either of solely 1-DoF or of both 1- and 2-DoF contractions, depending on the estimation scenario, as described below.

Two estimation scenarios were considered, both utilizing a predefined set of tasks from which the synergies were extracted. The extracted synergies were then used for calculating the neural inputs of test data. Since, for each subject, eight repetitions of each task were recorded, different training sets could be created for each subject.

In the first scenario (2-DoF training), the estimator model was trained (at medium level) and tested (at low level) using both single and combined DoF tasks. The training set of this scenario consisted of all repetitions of all 50% MVC 1- and

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2-DoF tasks. In the second scenario (1-DoF training), the 2-DoF tasks were eliminated from the training set, making it more practical in terms of the time and effort required of an amputee to train the system. This presents a more challenging estimation scenario, as the force estimator must generalize to 2-DoF tasks. However, the test set still contained both 1- and 2-DoF contractions.

The performance of force estimation analysis using synergies was investigated, and compared to that of using the channel-based mean absolute values (MAVs) of the EMG as inputs to the ANN.

The ability of the ANN to estimate force was quantified using the coefficient of determination (R^2) and root-mean-square error (RMSE). Here, RMSE is defined as the error between the actual and estimated force.

2.4.2 Repeatability and robustness of muscle synergies

The repeatability of synergy patterns is defined here to describe the consistency of results when extracting synergy patterns from the same set of tasks during multiple runs of the extraction algorithm. This repeatability test was conducted within one experiment and across different repetitions of the same tasks of the same force level.

The repeatability of the synergies was examined by extracting them from predefined sets of tasks. All tasks were included and each set contained two repetitions of low- or medium-contraction tasks. Therefore, for each subject, four sets were created; two containing only 25% MVC tasks and two containing only 50% MVC tasks. The synergies were extracted from these four sets for each subject to determine how repeatable they are in different repetitions of tasks under the same conditions.

Generally, a system is robust when it resists change without a need to adapt its initial configuration. Here, the robustness of synergy sets against the force change was tested and their ability to cope with changes in force levels in force estimation was examined. This means that for a set of tasks, changing the force level of the tasks should not affect the synergy patterns significantly. This robustness examination also can be extended to other variations such as electrode placement and electrode-skin impedance.

To examine this robustness, the four sets were used. Here, the difference between the extracted synergies from these tasks and their correspondent coefficients was studied.

2.4.3 Statistical analysis

An analysis of variance (ANOVA) with factors Synergies and MAV was performed on the each performance metric (R^2 and RMSE), with *p*-values less than 0.05 considered significant. Results are provided as means ± standard error across subjects.

3. Results and discussion

3.1 Repeatability and robustness of muscle synergies

Figure 2(a) (the first two rows) shows the synergies extracted from two low-contraction sets for two of the subjects. As shown, the synergies extracted from the base sets are almost

the same. This was typical for each subject, demonstrating good repeatability of the synergies. To quantify this, the correlation between the synergies extracted from each base set and the average of the results for all subjects was calculated. The correlation was 0.9934 ± 0.005.
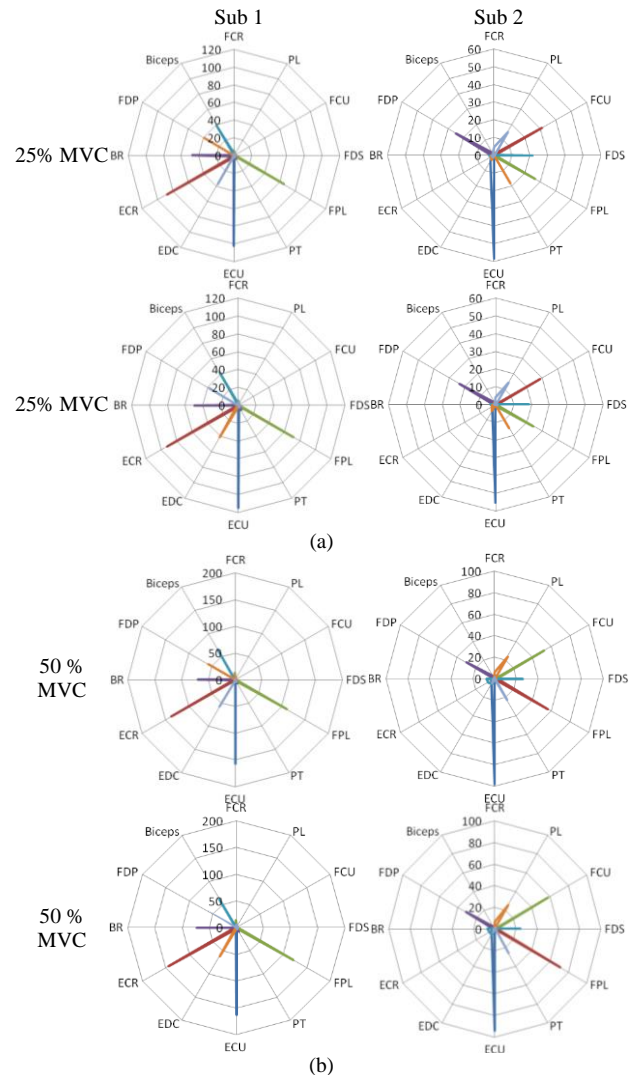

Figure 2. Comparison of synergies extracted from (a) two 25% MVC base sets and (b) two 50% MVC base sets for two subjects. The y (radial) axis measures the synergies magnitudes and has arbitrary units.

The same examination was performed for all eight subjects. Comparing the rows of Fig. 2(a) with those of Fig. 2(b), the synergies are scaled but their patterns are fairly consistent across different force levels. The correlation coefficients calculated between the synergy patterns of low- and high-contraction sets were very close to unity (the average was 0.9948 ± 0.004), which shows a strong linear relation between the two synergy sets and supports the robustness of synergies against force change. Since synergy analysis involves decomposing the EMG into the product of the synergy matrix and the neural inputs, this suggests that the estimated neural inputs may be effective in estimating force levels.

3.2 Force estimation

For the simple estimation problem (Scenario 1: 2-DoF training), the average (across subjects) of RMSE was 0.76 ± 0.42 and 0.88 ± 0.53 ($p = 0.002$) using synergies and MAVs, respectively. The average of R^2 was 0.84 ± 0.08 when using synergies and 0.84 ± 0.10 ($p = 0.024$) when using MAVs. Figure 3 shows the result of force estimation using six neural inputs for a sample segment of data including wrist extension and power grip performed by one subject. Figure 4 shows the RMSE and R^2 values averaged across all the subjects.
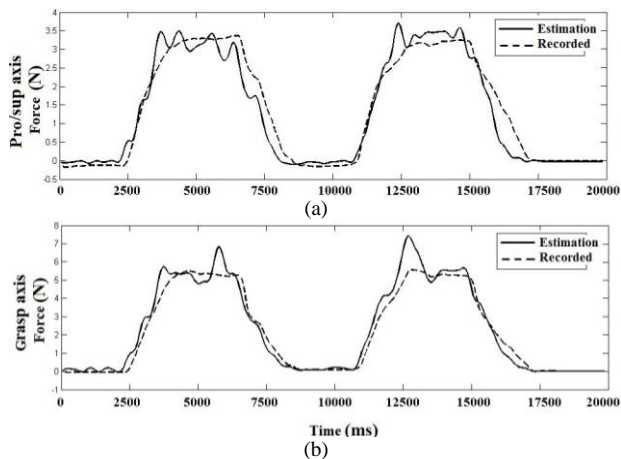

Figure 3. Sample (a) wrist extension and (b) power grip forces estimated using six neural inputs for a sample set of two repetitions. The illustrated force values are already down-sampled by a window length of 200 ms and in increments of 50 samples. The units of RMSE are the same as those of force measurements (N).
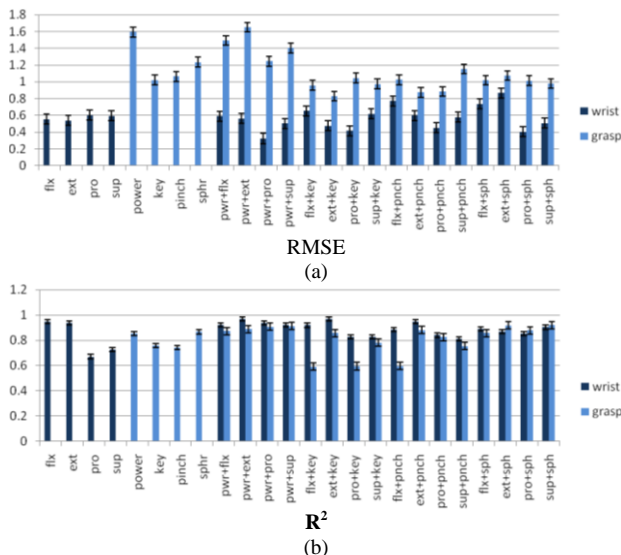

Figure 4. RMSE and R^2 values of force estimation in the 2-DoF training problem using synergies. The results are averaged across all eight subjects. The blue bars show the values associated with each plot for the wrist force axis and the red bars show those for the grasp force axis.

As can be seen in Fig. 4, generally better results were achieved in wrist force estimation than in grasps. The reason for this is likely that hand articulations distribute force across

multiple fingertips, and thus a consistent estimate of grasp force is difficult. Another source of error may be the low accuracy of the force measurements using FSRs. These sensors are nonlinear and they drift during the measurements. Also, subjects' fingers could have slipped off one or a few sensors while performing the tasks. However, the relatively high R^2 values still show that the estimation results can be acceptable, particularly in 1-DoF tasks, considering the fact that only one feature of the EMG signal is being used for estimating force.

Figure 5 compares the results obtained using synergies with those obtained using MAVs. The results show that synergies are able to estimate the force and in a majority of the tasks outperform MAVs in force estimation. Performing multivariate ANOVA on RMSE and R^2 showed that the methods are significantly different ($p < 0.05$) and that the results achieved by synergies are better.
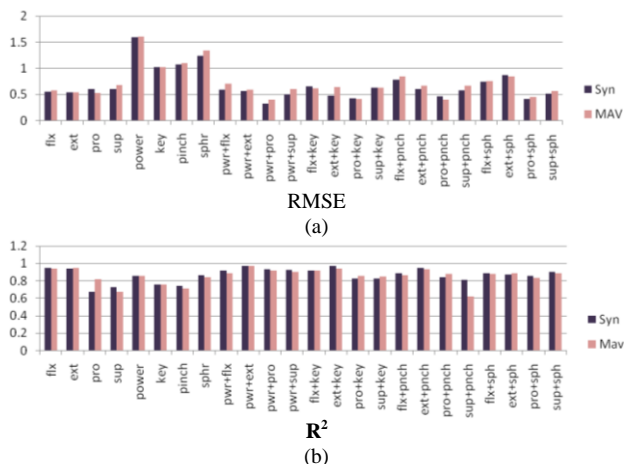

Figure 5. Comparison of results obtained using synergies with those obtained using MAVs in 2-DoF training problem. The results are averaged across all the subjects.

These results can be explained by the fact that the muscle synergies and their associated neural inputs show how different muscles co-activate in performing different tasks and describe their relative involvement in each task independent from the force level produced. This is an important factor that makes the muscle synergies a powerful input for force estimation in proportional control.

In the more challenging estimation problem (Scenario 2: 1-DoF training), the average across subjects of R^2 was 0.76 ± 0.22 when using synergies and 0.52 ± 0.49 when using MAVs, showing a significant difference ($p = 0.002$). RMSE was 0.90 ± 0.43 and 1.17 ± 0.64 for synergies and MAVs, respectively ($p = 0.002$).

Figure 6 shows the results obtained using synergies and compares them to those obtained using MAVs. The first thing that can be seen in the figure is that the force estimation was more accurate for 1-DoF tasks in comparison with the combined tasks. This was expected since the combined tasks were unknown to the model and estimating the force produced during those tasks from the signals associated with them is more challenging for the model. However, the relatively high R^2 values for many of the combined task profiles show that the model trained with the synergies of only 1-DoF tasks has the

potential to be used for force estimation in more complex and untrained tasks. The large estimation error, shown in Fig. 3, can be the result of scaling and/or delay in estimation with respect to the target. It is possible that this mismatch could be accommodated using an estimator with a temporal component, such as a time-delay neural network.
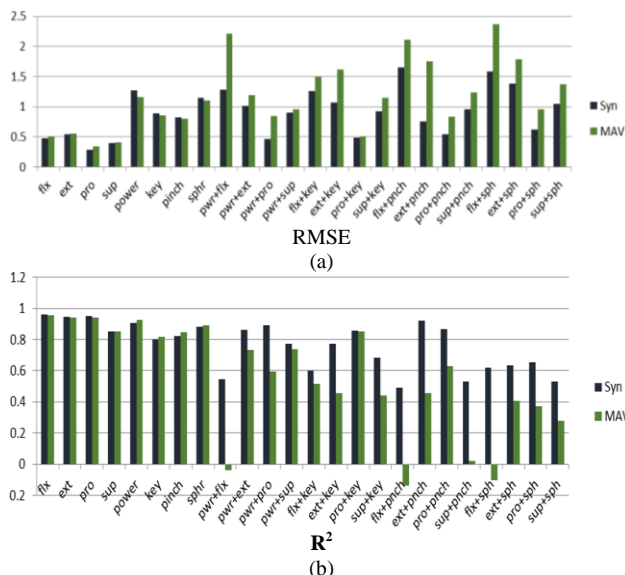

Figure 6. Comparison of results obtained using synergies with those obtained using MAVs in 1 DoF training problem. The results are averaged across all the subjects.

Another interesting observation from Fig. 6 is that while the results obtained using synergies and MAVs are nearly the same for 2-DoF training, synergies clearly outperform MAVs for 1-DoF training. These results explain that the neural inputs extracted from 1-DoF tasks contain important information that can be used to estimate the force produced during simultaneous tasks. This advantage of using synergies is supported by the fact that in the complex problem, the R^2 of only 4 out of 16 complex tasks was below 0.6, and all of them were above 0.5. Also, the model was trained and tested for various tasks and various subjects and the results were consistent across all these situations, proving that the results were not due to a random factor or limited to a particular data set or task. This suggests that the superposition property of muscle synergies allows the neural inputs to be effective for force estimation of more complex, multi-DoF tasks.

4. Conclusion

The muscle synergies extracted from a set of wrist and hand tasks demonstrated good repeatability for different repetitions of the same tasks and were quite robust across different force levels. The results indicate that muscle synergies show good progress toward force estimation of multi-DoF tasks. The R^2 values demonstrate that neural inputs outperform MAVs in multi-DoF force estimation. When tested with an unknown force level, the neural inputs outperformed MAVs, particularly when trained with a practical protocol of 1-DoF contractions. This demonstrates that synergies have good potential to be used

in estimating the force produced during multi-DoF force-varying tasks, which can be a valuable step toward improving proportional control of prostheses.

Furthermore, the number of neural inputs for force estimation are fewer than the number of muscles involved in the movement, reducing the dimension of the estimation model, and thus the computational requirements.

Acknowledgments

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