

# A PILOT STUDY OF TWO DEGREES OF FREEDOM DYNAMIC EMG-FORCE AT THE WRIST USING A MINIMUM NUMBER OF ELECTRODES

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**Abstract**—Myoelectric upper-limb prostheses are generally limited to control of one degree of freedom (DoF) at a time when proportionally actuating two upper-limb devices (e.g., hand-wrist). Mode switching is then used between the two devices. Users would greatly prefer an ability to control both DoFs simultaneously, independently and proportionally (SIP control). Researchers have previously studied 2-DoF SIP control via EMG-force tasks in able-bodied subjects (as well as limb-absent), showing feasibility using high density EMG electrode systems. These high-density systems are not practical for fielded prosthetic devices, thus recent research has studied 2-DoF EMG-force using a small number of commercial electrodes. We previously reported 2-DoF EMG-force results at the wrist using a *minimum* number of electrodes and *static* contractions—constant-posture, slowly force varying. Herein, we report pilot results from five able-bodied subjects with the experimental conditions expanded to constant-posture force-varying (*dynamic*) conditions. We found that the minimum number of electrodes for 2-DoF EMG-force at the wrist was four, when selected using backward stepwise selection from a pool of 16 electrodes. The average RMS errors ranged from 6.0–16.3% maximum voluntary contraction, depending on the attempted motions and the training-testing strategy used. This technique is promising. Evaluation in a larger sample and by limb-absent subjects in a prosthesis control task is suggested as necessary future work.

## I. INTRODUCTION

Many patients with transradial upper-limb absence use electromyogram (EMG) signals from residual forearm muscles to control the functions of a powered prosthetic wrist and/or hand [1–3]. Current commercial EMG-controlled prostheses that proportionally control motor speed are limited to control of one degree of freedom (DoF) at a time [2], which is considered a substantial limitation [4]. To provide advanced control, pattern recognition techniques have been introduced to select between a small set of pre-programmed hand (or hand-wrist) actions [5–10]. Multi-joint movement can be programmed, but the action is still only 1-DoF in nature. Kuiken and colleagues have used targeted muscle reinnervation surgery to realize simultaneous, independent and proportional (SIP) control of multiple upper limb prosthetic devices [11, 12]. However, the high cost, invasiveness of the surgery and extended recovery period (3–6) months are a barrier to more general use.

Researchers have studied upper-limb prosthesis SIP control using high density electrode arrays [13–15]. While showing

scientific feasibility, such arrays are not practical for use with commercial prosthetic devices. Nonetheless, this research has led to studies in which progressively fewer conventional surface EMG electrodes were applied [16–22].

Recently, we furthered this vein of research by investigating the *minimum* number of electrodes necessary for EMG-force models of two wrist DoFs, studying ten able-bodied and three limb-absent subjects [22]. This initial investigation was necessarily limited in scope, but was intended as a starting point to progress to 2-DoF EMG-based SIP control in a hand-wrist prosthesis. We studied fixed-posture contractions that were essentially *static* (slowly force-varying), to avoid the complexity of EMG-force dynamics. For the able-bodied subjects, four backward-selected electrodes provided performance that was statistically indistinguishable from the full 16 electrodes. In the research described herein, we extend this prior work to fixed-posture force-varying contractions, and extend our EMG-force models accordingly to account for dynamics.

## II. METHODS

### A. Experimental Methods

Five abled-bodied subjects provided written informed consent for an experiment approved by New England IRB (Newton, MA). Data were acquired at Liberating Technologies, Inc. (Holliston, MA).

The experimental apparatus mainly consisted of three parts. Firstly, a six-DoF load cell (MC3A-100 transducer with Gen 5 signal conditioner, AMTI, Watertown, MA) measured extension-flexion (Ext-Flx), radial-ulnar deviation (Rad-Uln) and pronation-supination (Pro-Sup) force/moment of the wrist, with a hand-shaped thermoformable plastic splint attached to the load cell to fix the pose of the dominant hand (Fig. 1). Secondly, 16-channel bipolar surface EMG electrodes were placed around the forearm to measure EMG signals. Each electrode pair consisted of 5 mm diameter, stainless steel hemispherical contacts with 1 cm edge-to-edge separation. An amplifier (Liberating Technologies, Inc. BE328; 30–500 Hz pass band, CMRR>100 dB over the pass band) processed the differential EMG signal and selectable gain was applied. The average ratio of resting RMS EMG to the RMS EMG

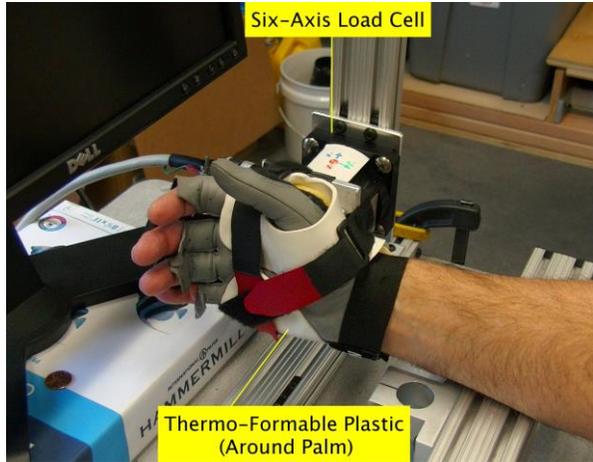


Fig. 1. Experimental apparatus. Dominant hand was tightly secured via thermo-formable plastic and Velcro to six-axis load cell. Sixteen electrodes (not visible) were secured about the distal aspect of the dominant forearm.

at 50% maximum voluntary contraction (MVC), expressed as a percentage, was  $8.1 \pm 5.4\%$ . Thirdly, two arrowheads were displayed on a computer screen. One arrowhead displayed the load cell measurements, with  $x$ -axis location corresponding to Ext-Flx force,  $y$ -axis location to Rad-Uln force and rotation to Pro-Sup moment. The other arrowhead used a different color to display a computer-controlled target to guide the subject to perform each task. The three load cell signals and 16 EMG signals were sampled at 2048 Hz with 16-bit resolution.

**Experimental Preparation:** The dominant forearm skin surface of a subject was wiped using alcohol prep pads and electrode gel was applied. EMG electrodes were placed on a row transversely about the forearm at equal inter-electrode distances, with the mid-point of each electrode 5 cm distal from the crease of the elbow. Each electrode was oriented with the bipolar contacts along the long axis of the forearm. A reference electrode was gelled and secured on the ventral forearm, just distal to the row of active electrodes. Then the subject sat on the apparatus with the dominant hand cuffed to the load cell by a thermo-formable plastic splint (hand was vertical to the floor) to maintain a constant posture. The wrist was in a neutral position with respect to the hand and the elbow was supported at the olecranon process. The shoulder was flexed  $45^\circ$  forward from the anatomical position along the sagittal plane.

**MVC Trials:** Subjects were provided warm-up preparation before the contraction trials and 2–3 minutes rest between each contraction to prevent muscle fatigue. MVC was measured for each DoF (Ext-Flx, Rad-Uln and Pro-Sup). Subjects progressively increased contraction for 2–3 seconds and the plateau level of their force/moment maximum was their MVC. Signal noise levels were also evaluated by rest trials.

**One-DoF Dynamic Tracking Trials:** Each of the four DoFs

was investigated separately. For Ext-Flx, the target arrowhead randomly moved between  $\pm(|30\%MVC Ext|+|30\%MVC Flx|)/2$ . The movement of the arrowhead was a white, uniform process with a band-limit of 0.75 Hz; an arrowhead speed of movement that could be tracked by subjects. The other arrowhead displayed as feedback the load cell force/moment of the active DoF only. The 16 EMG channels and all load cell data were recorded for 4 trials of 40s duration. Identical trials were conducted for the other two DoFs ( $4 \times 3 = 12$ , 40 s trials overall). The order of presentation of the DoFs was randomized between subjects.

**Two-DoF Dynamic Tracking Trials:** All three combinations of DoF pairs (Ext-Flx & Rad-Uln, Ext-Flx & Pro-Sup, and Rad-Uln & Pro-Sup) were tracked for tests. Each trial involved two different DoFs simultaneously—the target arrowhead moved with two independent random instances, and the feedback arrowhead tracked both DoFs simultaneously. (The third DoF was suppressed.) Each of the three combinations had four trials of 40s duration ( $4 \times 3 = 12$ , 40 s trials overall).

### B. Methods of Analysis

**Pre-Processing:** All data processing was computed offline using MATLAB, with function “filtfilt()” (non-casual, zero-phase, forward and reverse filtering technique) used for all filtering. Each EMG channel was highpass filtered (5<sup>th</sup> order Butterworth, cut-off at 15 Hz) to attenuate motion artifacts, notch filtered at 60 Hz with 1 Hz bandwidth to cancel the power line interference, and then rectified. Each rectified signal was lowpass filtered at 16 Hz (Chebyshev Type 1 filter, 9<sup>th</sup> order, 0.05 dB peak to peak passband ripple) and downsampled from 2048 Hz to 40.96 Hz. This smoothed EMG standard deviation estimate ( $EMG\sigma$ ) made the signal suitable for system identification of  $EMG\sigma$ -force dynamic models. Each force/moment signal (Ext-Flx, Rad-Uln and Pro-Sup) was normalized by  $(|MVC \text{ of one direction}|+|MVC \text{ of opposite direction}|)/2$  and then similarly decimated. [22]

**One-DoF Dynamic Models:** For Ext-Flx, a linear least squares method used two training trials to fit the  $EMG\sigma$ -force/moment dynamic linear model:

$$T_{E-F}[m] = \sum_{q=0}^Q \sum_{e=1}^E c_{e,q} EMG\sigma_e[m-q], \quad (1)$$

where  $T_{E-F}[m]$  was Ext-Flx force at decimated sample index  $m$ ,  $q$  was the order of the linear dynamic model,  $e$  was the EMG channel index,  $c_{e,q}$  were the fit coefficients, and  $EMG\sigma_e$  was the EMG standard deviation estimate for channel  $e$ . The analogous model was utilized for the other two DoFs. The maximum lag of the model was selected as  $Q=20$  [23]. The pseudo-inverse technique was used to regularize the least squares fit, in which singular values

were removed if the ratio of that singular value to the largest singular value in the design matrix was less than a tolerance value [24]. A tolerance value of 0.01 was selected [22, 23]. The remaining two trials were used for testing, computing the RMS error between the measured force and EMG-estimated force (using the coefficients fit from the training trials). Then the training and testing sets were switched for two-fold cross-validation, which was selected for computational efficiency because of the model correlations of the four remaining cross validation folds. The average RMS test trial error from the two cross-validation folds is reported. The backward stepwise technique was applied for electrode selection. Initially from 16 electrodes, the channel was excluded when its absence resulted in the lowest RMS error step by step until only one electrode remained. Only training data were used for backward stepwise selection decisions. For comparison, we additionally computed the multivariate  $R^2$  index on the test trails [16], which is also commonly used to assess model error. Identical analysis was performed on the other two DoFs.

**Two-DoF Dynamic Models:** Two-DoF dynamic models were separately trained and tested for all three combinations of two simultaneous DoFs. The model of (1) was used for both DoFs, with distinct fit coefficients per DoF. The same pseudo inverse tolerance value and maximum lag were used, as was backward stepwise selection of electrodes. Three different training paradigms (training with 1-DoF trials, with 2-DoF trials, or with both 1- and 2-DoF trials) and two testing paradigms (testing on 1-DoF trials or on 2-DoF trials) were applied to estimate the performance, as different training strategies represented different methods by which real prostheses might be trained, and different testing strategies evaluate if 2-DoF models retain good performance when encountering 1-DoF tasks.

**Statistics:** Repeated measures ANOVA (RANOVA) tested factor and level differences (SPSS 22), using a significance level of  $p = 0.05$ . If data violated the assumption of sphericity, the degrees of freedom for the effect was adjusted: for  $\epsilon < 0.75$  with the method of Greenhouse-Geisser, for  $\epsilon > 0.75$  with the method of Huynh-Feldt [25]. *Post hoc* pair-wise comparisons used paired  $t$ -tests with Bonferroni correction. Only test trial results are reported.

### III. RESULTS

#### A. One-DoF Models

Fig. 2 shows sample time-series EMG-force test results for the 1-DoF models. Fig. 3 shows summary RMS error results as a function of number of electrodes selected. Performance was calculated for 1–16 numbers of electrodes, separately for each of the 3 DoFs. Using all the RMS error results of 1-DoF models, a two-way RANOVA (factors: DoF, number of electrodes) indicated that only number of electrodes had a significant effect on performance [ $F(1.5, 6.0) = 67, p_{GG} <$

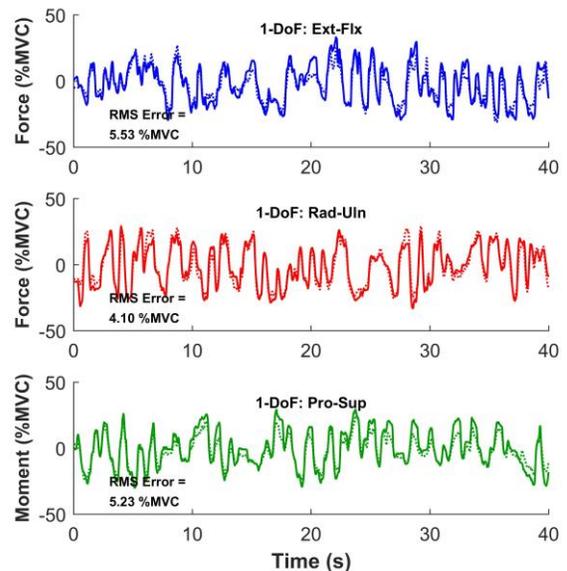


Fig. 2. Example time-series plots of 1-degree-of-freedom models, two electrodes (Subject 05, Trials 71, 74, 77). Solid lines are actual forces/moment, dotted lines are EMG-estimated.

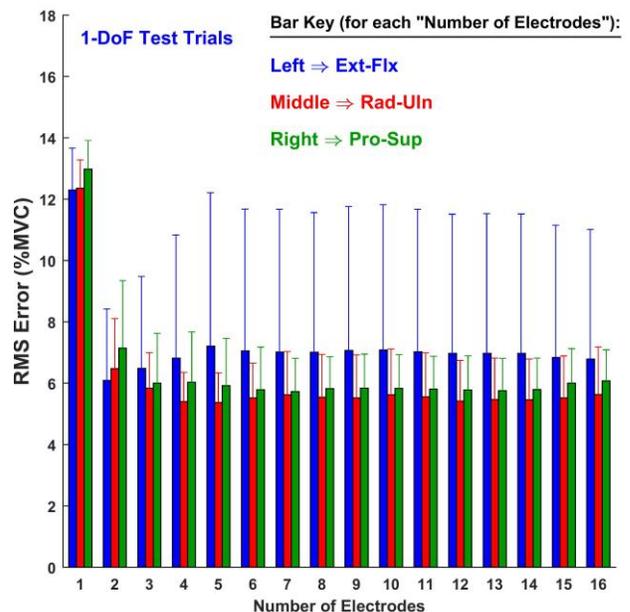


Fig. 3. Summary RMS error results: 1-degree-of-freedom models, five subjects. Error lines show one standard deviation above the mean.

$10^{-4}$ ], without interaction. Post hoc comparison found that only one electrode had higher error than 2–4, 6–8 and 12–15 electrodes ( $p < 0.048$ ), and there were no differences in performance when comparing 2 or more electrodes. Table I shows the RMS errors for 2 backward-selected electrodes (typical in a commercial 1-DoF prosthesis controller) and the  $R^2$  index values corresponding to these RMS errors, for each DoF.

#### B. Two-DoF Models

Two-DoF models separately estimated 2 DoFs models for

Ext-Flx & Rad-Uln, Ext-Flx & Pro-Sup, or Rad-Uln & Pro-Sup. Fig. 4 shows sample time-series EMG-force test results during 2-DoF trials and Fig. 5 shows summary RMS error results. Table I (except for the top row) shows RMS errors and the  $R^2$  index values for the different training/testing strategies.

**Two-DoF Models Assessed on 1-DoF trials:** A three-way RANOVA (factors: DoF, number of electrodes, training conditions) was computed and all three factors were significant, but training condition interacted with number of electrodes:  $[F(1.7, 6.7) = 6.2, p_{GG} = 0.034]$ . As training condition had the lowest degrees of freedom, separate two-way RANOVAs were conducted with each of the three training conditions fixed.

When training with only 1-DoF trials, only number of electrodes was significant  $[F(1.7, 6.9) = 76, p_{GG} < 10^{-4}]$ , with no interaction. *Post hoc* comparison found that 1 electrode always had higher errors than 3, 7–10, 12–14 and 16 electrodes ( $p < 0.05$ ), and there was no difference when comparing 2 and more electrodes

Results when training with only 2-DoF trials only found a significant difference for DoF  $[F(2, 8) = 5.8, p = 0.027]$ , without interaction. *Post hoc* tests found no differences.

The two-way RANOVA when training with both 1- and 2-DoF trials found that only number of electrodes was significant  $[F(1.9, 7.6) = 117, p_{GG} < 10^{-5}]$ , without interaction. *Post hoc* comparison found that 1 electrode exhibited higher error than 6 and more ( $p < 0.04$ ); 2 electrodes higher than 7 and more ( $p < 0.045$ ); and 3 electrodes higher than 9 and 10 ( $p < 0.04$ ). There were no differences when comparing 4 and more electrodes.

As the RMS error vs. number of electrodes trended to a steady state above 4–5 electrodes, the number of electrodes was fixed at 4 and a two-way RANOVA was computed with factors of DoF and training condition. Both the DoF  $[F(2, 8) = 9.9, p = 0.007]$  and training condition  $[F(1.0, 4.1) = 62, p_{GG} < 10^{-3}]$  were significantly different, without interaction. *Post hoc* analysis only found that Ext-Flx & Rad-Uln always exhibited lower errors than Rad-Uln & Pro-Sup ( $p = 0.046$ ) and training with only 2-DoF trials exhibited higher error than the other two conditions ( $p < 0.005$ ).

**Two-DoF Models Assessed on 2-DoF trials:** A three way RANOVA showed that all three factors were significant, but number of electrodes and training condition interacted  $[F(2.2, 9.0) = 4.9, p_{GG} = 0.034]$ . Thus, three two-way RANOVAs were computed with each of training conditions fixed, similar to above.

When training with only 1-DoF trials, there was no significant difference found, without interaction.

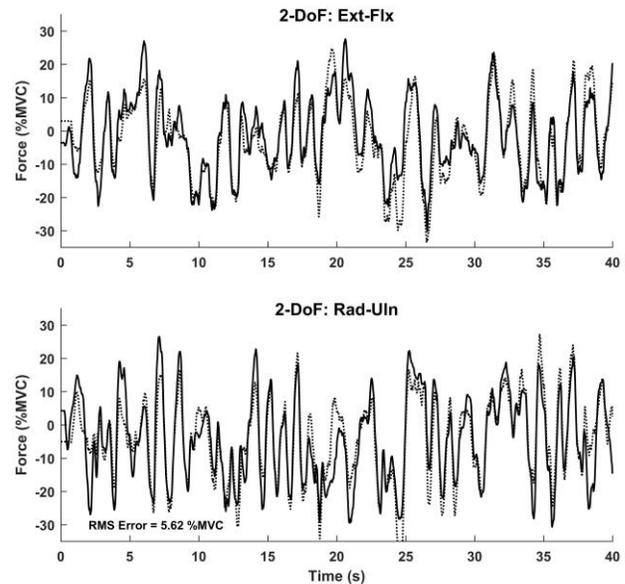


Fig. 4. Example time-series plots of 2-degree-of-freedom models from subject 05, trial 81 (four electrodes). Key: solid lines=actual forces, dashed=estimated; black=Ext-Flx, blue=Rad-Uln. Four EMG channels and training from both 1- and 2-DoF trials.

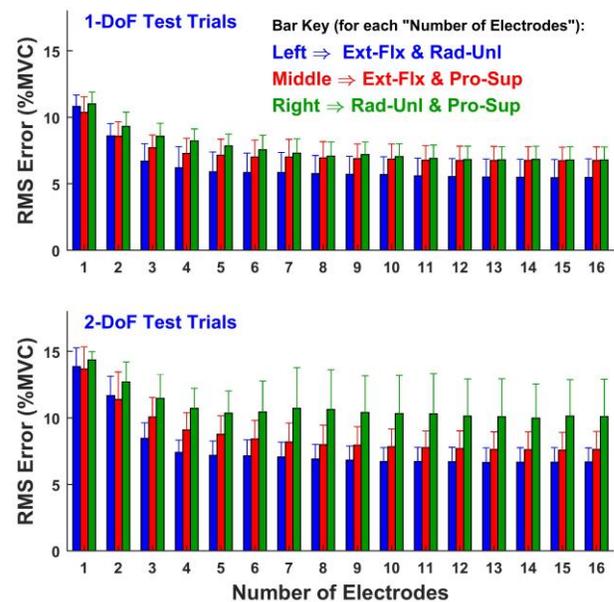


Fig. 5. Summary results: 2-degree-of-freedom (DoF) models, five subjects. Models trained from both 1- and 2-DoF trials, Top: testing on 1-DoF trials. Bottom: testing on 2-DoF trials. Error lines show one standard deviation above the mean.

Results when training with only 2-DoF trials found that only number of electrodes was significant  $[F(1.2, 5.0) = 25, p_{GG} = 0.003]$ , without interaction. *Post hoc* comparison found no significant differences between each level of number of electrode.

Results when training with both 1- and 2-DoF trials showed that only number of electrodes was significant  $[F(1.4, 5.7) = 45, p_{GG} = 10^{-3}]$ , without interaction. *Post hoc* analysis

TABLE I  
MEAN  $\pm$  STD. DEV. RMS ERRORS (%MVC, LEFT) AND CORRESPONDING  $R^2$  INDEX (RIGHT), FIVE SUBJECTS, BACKWARD SELECTED ELECTRODES

| Condition                              | DoF(s), RMS Error (%MVC)         |                                  |                                  | DoFs, $R^2$ Index (%)            |                                  |                                  |
|--|----------------------------------|----------------------------------|----------------------------------|----------------------------------|----------------------------------|----------------------------------|
|  | Ext-Flx                          | Rad-Uln                          | Pro-Sup                          | Ext-Flx                          | Rad-Uln                          | Pro-Sup                          |
| <b>1-DoF Models<br/>(2 electrodes)</b> |                                  |                                  |                                  |                                  |                                  |                                  |
| Assessed on 1-DoF trials               | 6.1 $\pm$ 2.3                    | 6.5 $\pm$ 1.6                    | 7.1 $\pm$ 2.2                    | 81 $\pm$ 11                      | 79 $\pm$ 9                       | 71 $\pm$ 21                      |
| <b>2-DoF Models<br/>(4 electrodes)</b> | <b>Ext-Flx &amp;<br/>Rad-Uln</b> | <b>Ext-Flx &amp;<br/>Pro-Sup</b> | <b>Rad-Uln &amp;<br/>Pro-Sup</b> | <b>Ext-Flx &amp;<br/>Rad-Uln</b> | <b>Ext-Flx &amp;<br/>Pro-Sup</b> | <b>Rad-Uln &amp;<br/>Pro-Sup</b> |
| Assessed on 1-DoF trials:              |                                  |                                  |                                  |                                  |                                  |                                  |
| Train with 1-DoF trials                | 6.0 $\pm$ 1.6                    | 7.1 $\pm$ 1.2                    | 7.6 $\pm$ 1.6                    | 69 $\pm$ 13                      | 57 $\pm$ 8                       | 50 $\pm$ 17                      |
| Train with 2- DoF trials               | 9.0 $\pm$ 2.5                    | 10.7 $\pm$ 1.1                   | 12.8 $\pm$ 1.6                   | 38 $\pm$ 20                      | 25 $\pm$ 13                      | 10 $\pm$ 8                       |
| Train with 1-, 2- DoF trials           | 6.2 $\pm$ 1.6                    | 7.4 $\pm$ 1.1                    | 8.1 $\pm$ 1.5                    | 66 $\pm$ 13                      | 52 $\pm$ 9                       | 44 $\pm$ 15                      |
| Assessed on 2-DoF trials:              |                                  |                                  |                                  |                                  |                                  |                                  |
| Train with 1-DoF trials                | 9.8 $\pm$ 2.6                    | 11.3 $\pm$ 2.2                   | 16.3 $\pm$ 6.7                   | 53 $\pm$ 15                      | 41 $\pm$ 23                      | 19 $\pm$ 21                      |
| Train with 2-DoF trials                | 6.7 $\pm$ 0.7                    | 7.8 $\pm$ 1.4                    | 10.8 $\pm$ 1.6                   | 78 $\pm$ 2                       | 72 $\pm$ 10                      | 45 $\pm$ 14                      |
| Train with 1-, 2-DoF trials            | 7.3 $\pm$ 1.1                    | 9.1 $\pm$ 1.5                    | 11.4 $\pm$ 1.5                   | 74 $\pm$ 4                       | 62 $\pm$ 12                      | 42 $\pm$ 14                      |

only found that 1 electrode exhibited higher error than 3 electrodes ( $p = 0.049$ ). There were no other differences.

Lastly, we also computed a two-way RANOVA (factors: DoF, training condition) fixing the number of backward-selected electrodes to four. We selected four electrodes for this comparison because Fig. 5 shows a trend that suggests improvements out to at least four electrodes, the low sample size likely contributed to a difficulty in finding statistical significance for more than 2 electrodes related to this trend, our prior work with a larger sample size suggests a statistical significance is supported with four electrodes [22], and this number of electrodes is preferred in a 2-DoF commercial prosthesis controller. Both DoF [ $F(2, 8) = 7.9, p = 0.013$ ] and training condition [ $F(1.0,4.1) = 12, p_{GG} < 0.024$ ] were significant, without interaction. *Post hoc* pairwise comparison for DoFs found that all three combinations had no significant difference. Training with only 2-DoF trials always exhibited lower errors than with both 1- and 2-DoF trials ( $p = 0.026$ ).

#### IV. DISCUSSION

In a pilot study, we evaluated 1-DoF models primarily as a basis of comparison to existing proportional controllers and to our own 2-DoF results. For 1-DoF models, our results showed that the RMS error was much higher when only one electrode was retained. The main reason is that  $EMG\sigma$  is a unipolar (non-negative) measurement, while any wrist force/moment has two contraction directions (e.g., extension and flexion), which means the force/moment is a bipolar quantity. Therefore, poor performance can be expected when a linear model is used. This conclusion is consistent with our previous study [22]. (Note that even one electrode performed better in estimating force than ignoring the EMG altogether—an average RMS error of 17.3% would result if the 1-DoF target was compared to a fixed estimate of 0 %MVC.) Furthermore, our results established

the findings that no significant improvement was achieved when using more than two electrodes. We found no significant differences as a function of DoF. However, Table I shows a trend for higher Pro-Sup RMS error. Some previous studies have found that EMG-force using the Pro-Sup DoF was more challenging [16, 18]. One possible reason is that the muscles producing Pro-Sup contraction reside deeper within the forearm, thus being less accessible to surface EMG recordings [18]. A larger sample size might substantiate this relationship with our protocol, although it is unclear if such differences would have a clinically significant impact on prosthesis performance.

For 2-DoF models, the suggested minimum requirement of conventional electrodes increased to four, compared with 1-DoF models (although summary plots in Fig. 3 and Fig. 5 show more gradual performance changes as a function of the number of electrodes). This conclusion was intuitive that more electrodes were required to represent the relationship between  $EMG\sigma$  and force/moment, due to the increased complexity when one more DoF was involved. There were no substantive differences as a function of DoF, perhaps due to the limited statistical power ( $N=5$  subjects). The RMS errors of 2-DoF models varied from 6.0% to 16.3% according to different DoF combinations and training-testing strategies. For different training-testing strategies, the performance of 1-DoF tasks were initially evaluated since a 2-DoF prosthesis controller still needs to be operated for 1-DoF tasks. When assessed on 1-DoF trials, the performance of training with 2-DoF trials and using four electrodes was *poorer* than the other two strategies. On the other hand, when assessed on 2-DoF trials, the performance of training with 2-DoF trials and using four electrodes was *better* than the other two strategies. Therefore, training with both 1- and 2-DoF trials is recommended since both 1-DoF and 2-DoF tasks would be performed when a 2-DoF prosthesis controller is operated. Of course, the interplay

between these EMG-force errors due to training might not be entirely indicative of performance in a fielded prosthesis, for which simpler (and less time consuming) calibration tasks are desired.

A prime limitation of this work is its small sample size ( $N=5$  subjects). With this small sample, our statistical results are biased towards non-significance due to the lack of statistical power. For example, a few of our significant RANOVA results produced *post hoc* paired comparisons (with Bonferroni correction) in which none of the comparisons was significant. Multiple comparisons with Bonferroni correction are easy to apply and can reduce the risk of a Type I error. However, the disadvantages of this procedure are that the statistical power to reject an individual hypothesis is too low, and controlling Type I error leads to the increasing of Type II error, making it hard to find significant results (particularly with small sample sizes) [26]. Other limitations include: laboratory performance of an EMG-force task does not fully represent performance of an algorithm in a fielded prosthesis, low EMG-force errors do not easily translate into predictive performance of a prosthetic controller, we only studied able-bodied subjects, we limited our contractions to those at a fixed pose and conducted during a single experimental session, and that our backward selection technique might not find a unique (or global) minimum [22].

In spite of these limitations, these methods and results contribute towards the feasibility of a practical 2-DoF SIP controller. Of course, the various algorithms implemented offline in this work will need to be translated into appropriate online equivalents. Note that we studied three candidate DoF pairs—in practice, the best performing of these pairs would be selected by a prosthetist for use by each specific prosthesis user. Our results showed little preference as to which pair might be best, on average; the only significant *post hoc* result for DoF was that Ext-Flx & Rad-Uln exhibited lower errors than Rad-Uln & Pro-Sup when 2-DoF models were assessed on 1-DoF tasks with the number of electrodes fixed at four.

## V. CONCLUSION

This pilot study has investigated both 1- and 2-DoF *dynamic* EMG-force at the wrist using as few conventional electrodes as possible. This study extends our prior research [22], which only considered *static* contraction (and, thus, non-dynamic models). Our results showed that the minimum requirement of conventional electrodes was two for 1-DoF and four for 2-DoFs. For 1-DoF, the average  $\pm$  std. dev. RMS errors were  $6.1 \pm 2.3\%$ ,  $6.5 \pm 1.6\%$  and  $7.1 \pm 2.2\%$  for Ext-Flx, Rad-Uln and Pro-Sup, respectively, using two electrodes. For 2-DoFs, the average RMS error of the three possible pairs of 2-DoF contractions ranged from 6.0% to 16.3% MVC, depending on different training-testing strategies using four electrodes. Our findings

revealed that 2-DoF simultaneous EMG-force at the wrist may be feasible by utilizing a very small number of conventional electrodes. The technique is promising for 2-DoF wrist prosthesis control.

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## REFERENCES

- [1] R. W. Mann and S. D. Reimers, IEEE Trans. Man-Mach. Sys., vol. 11, no. 1, pp. 110–115, 1970.
- [2] P. Parker, K. Englehart, and B. Hudgins, J. Electromyogr. Kinesiol., vol. 16, pp. 541–548, 2006.
- [3] D. Farina, et al., IEEE Trans. Neural Sys. Rehabil. Eng., vol. 22, no. 4, pp. 797–809, 2014.
- [4] D. J. Atkins, D. C. Y. Heard, and W. H. Donovan, J. Prosthet. Orthot., vol. 8, no. 1, pp. 2–11, 1996.
- [5] D. Graupe and W. K. Cline, IEEE Trans. Sys. Man Cyber., vol. 5, no. 2, pp. 252–259, 1975.
- [6] B. Hudgins, P. Parker, and R. N. Scott, IEEE Trans. Biomed. Eng., vol. 40, no. 1, pp. 82–94, 1993.
- [7] R. Boostani and M. H. Moradi, Physiol. Meas., vol. 24, pp. 309–319, 2003.
- [8] K. Englehart and B. Hudgins, IEEE Trans. Biomed. Eng., vol. 50, no. 7, pp. 848–854, 2003.
- [9] M. A. Powell, R. R. Kaliki, and N. V. Thakor, IEEE Trans. Neural Sys. Rehabil. Eng., vol. 22, no. 3, pp. 522–532, 2014.
- [10] Coapt, LLC, 222 W. Ontario St., Suite 300, Chicago, IL. (accessed 6 June 2015). Available: <http://www.coaptengineering.com>.
- [11] T. A. Kuiken, et al., Prosthet. Orthot. Int., vol. 28, pp. 245–253, 2004.
- [12] T. A. Kuiken, et al., J. Am. Med. Assoc., vol. 301, no. 6, pp. 619–628, 2009.
- [13] S. Muceli and D. Farina, IEEE Trans. Neural Sys. Rehabil. Eng., vol. 20, no. 3, pp. 371–378, 2012.
- [14] P. Liu, et al., IEEE Sig. Proc. Med. Biol. Symp., 2013.
- [15] S. Muceli, N. Jiang, and D. Farina, IEEE Trans. Neural Sys. Rehabil. Eng., vol. 22, no. 3, pp. 623–633, 2014.
- [16] N. Jiang, K. B. Englehart, and P. A. Parker, IEEE Trans. Biomed. Eng., vol. 56, no. 4, pp. 1070–1080, 2009.
- [17] J. L. Nielsen, et al., IEEE Trans. Biomed. Eng., vol. 58, no. 3, pp. 681–688, 2011.
- [18] N. Jiang, et al., J. NeuroEng. Rehabil., vol. 9:42, 2012.
- [19] A. Ameri, et al., IEEE Trans. Neural Sys. Rehabil. Eng., vol. 22, no. 6, pp. 1198–1209, 2014.
- [20] A. L. Fougner, O. Stavdahl, and P. J. Kyberd, J. NeuroEng. Rehabil., vol. 11:75, 2014.
- [21] S. Amsuess, et al., IEEE Trans. Neural Sys. Rehabil. Eng., vol. 24, no. 7, pp. 744–753, 2016.
- [22] E. A. Clancy, et al., J. Electromyogr. Kinesiol., vol. 34, pp. 24–36, 2017.
- [23] E. A. Clancy, et al., IEEE Trans. Biomed. Eng., vol. 59, no. 1, pp. 205–212, 2012.
- [24] W. H. Press, et al., "Numerical Recipes in C," 2nd ed. New York: Cambridge Univ. Press, 1994, pp. 671–681.
- [25] E. R. Girden, ANOVA: Repeated Measures. Sage Publications, 1992, p. 21.
- [26] D. C. Howell, Statistical Methods for Psychology, 7th Ed. Belmont, CA: Cengage Wadsworth, p. 366, 2010.