A Pilot Study Assessing Ipsilateral vs. Contralateral Feedback in EMG-Force Models of the Wrist for Upper-Limb Prosthesis Control

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***Abstract*—Many advanced EMG-based upper-limb prosthesis control methods require model training in which subjects produce supervised forces/movements. Since unilateral limb-absent subjects cannot produce forces/movements on their affected side, one technique (mirrored bi-lateral training) relates forces/motions produced on the sound side to EMG on the affected side. However, the efforts made by the phantom limb may not fully reflect those of the sound limb. To understand this issue, three able-bodied subjects produced mirrored bi-lateral forces during constant-posture contraction at the wrist. EMG-force models were formed for 1- and 2-degree of freedom tasks and results compared to previous trials in which ipsilateral training had been conducted. We found that contralateral training generally, but not always, produced errors (in percent maximum voluntary contraction) that were 6–56% larger than those found from ipsilateral training. Our results suggest that a substantial portion—but not all—of the errors found in mirrored tasks may be due to contralateral tracking errors. Further study with a larger population is indicated.**

Keywords—EMG, electromyogram, prosthesis, prosthesis control, myoelectric control, EMG signal processing

I. Introduction

Many people with transradial limb absence use electromyogram (EMG)-controlled, powered hand and wrist prostheses to provide partial functional replacement. Existing commercial EMG-controlled prostheses typically use EMG from the residual flexors and extensors of the forearm to actuate prosthetic hand closing and opening, respectively. Wrist rotation is not controlled simultaneously, rather some form of mode switching (via EMG or mechanical switch) is used to sequence between hand and wrist activation [1]. This lack of proportional, simultaneous and independent control represents a substantial limitation of existing upper-limb prosthetic systems [2].

To improve upper-limb prosthesis control, Kuiken and colleagues [3, 4] have developed targeted muscle reinnervation surgery, in which muscles of the chest wall are denervated, after which nerves formerly associated with the lost limbs are grafted to these chest muscles. Activation of the phantom limb causes actual contraction of chest muscles, providing proportional, simultaneous and independent control signals. The cost and lengthy rehabilitation (3–6 months) required by this technique may make it most appropriate for bilateral limb-absent patients and those with high-level unilateral limb absence. Alternatively, pattern recognition techniques have related EMG from the residual forearm to a set of preselected hand-wrist movements [1, 5-9]. Multiple-joint movement is possible, albeit still generally comprised of only one degree of freedom (DoF). This method recently became available in a commercial system (COAPT LLC, Chicago, IL).

For a large class of transradial limb-absent persons, there is a need for proportional, simultaneous and independent EMG-based prosthesis control using the residual forearm musculature. Several studies have addressed this problem, primarily in able-bodied volunteers. Initial studies largely focused on the scientific establishment of a hand/wrist EMG-force relationship. These studies applied high-density electrodes to the forearm (often 64^+ electrodes), studying finger forces/pose or wrist forces [10-12]. A convincing, multiple-DoF EMG-force relationship in the wrist was demonstrated in able-bodied subjects. Nonetheless, high-density electrodes were never intended for commercial prosthetic use.

In the past few years, research has focused on adapting the EMG-force modeling for use with conventional bipolar electrodes and commercial prosthesis systems [13-18]. Most modeling methods are supervised, thus some form of subject “output” (i.e., subject force, position or effort) must exist to which the (input) EMG signal is related. In persons with limb absence, finding an appropriate output is challenging, as no limb is available on the affected side to produce hand/wrist forces or movement. One method uses only the affected side and a target on the computer screen [15, 18]. The subject produces an effort in their phantom limb to match the effort associated with the location and/or orientation of the target. This method is direct, but does not provide any feedback.

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The interest of this work is in another training method known as mirrored bi-lateral (contralateral) contractions, in which the affected hand/wrist mirrors the contraction profile of the sound side hand/wrist [11, 14, 17-19]. EMG recordings from the affected side are related to the actual forces/ movements measured on the sound side. Feedback is available, but only from the contralateral side. This method is only available to those with unilateral limb-absence. Past research work suggests that performance when using the contralateral training approach is poorer than that found in identical tasks using an ipsilateral training approach [17, 18]. These past studies investigated forces in the wrist, applying 7–8 bipolar electrodes, performing specific tasks (1- and 2-DoF wrist movement or isometric attempted movement or sinusoidal contractions) using the coefficient of determination (R^2) for assessment. We have been studying constant-posture EMG-force in the wrist with either quasi-constant-force contractions that span ±30% maximum voluntary contraction (MVC) or band-limited uniform random dynamic force contractions that span this same force range. Our studies also reduce the number of bipolar electrodes used from 16 to 4 for 2-DoF tasks. A subset of three able-bodied subjects completed both ipsilateral training and mirrored bi-lateral (contralateral) training. Herein we compare their EMG-force performance with our assessment metric—RMS EMG-force error, normalized to MVC.

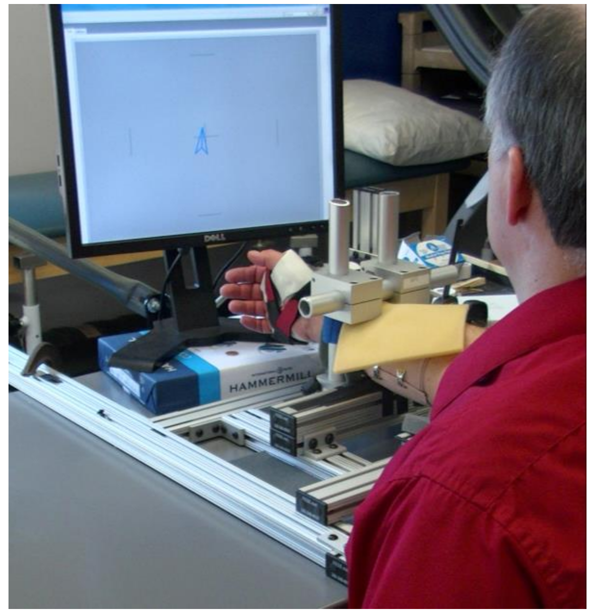

Fig. 1. **Ipsilateral** data collection apparatus. The dominant hand was tightly secured via a thermo-formable plastic splint and Velcro to a six-axis load cell. The wrist was maintained in a neutral position by a padded restraint. Sixteen electrodes (not visible) were secured about the proximal aspect of the forearm. Display screen is visible in front of the subject.

II. Methods

A. *Experimental Apparatus and Procedures*

Experiments and data analysis were approved by the New England IRB (Newton, MA) and the WPI IRB. Each of three male subjects (aged 25, 37 and 53 years) provided written informed consent. Each subject participated in two, half-day experiments on separate days, with ~6 months between the two sessions. Subjects performed ipsilateral training in the first session and contralateral training in the second session.

For the first experimental session (ipsilateral trials), skin about the proximal forearm of the dominant arm (right arm for each subject) was scrubbed with an alcohol wipe and electrode gel was massaged into the skin. Sixteen bipolar electrodes were mounted equidistant in a row, transversely about the forearm, each centered 5 cm distal from the elbow crease. One electrode pair was aligned at the most dorsal aspect. Each electrode pair consisted of 5 mm diameter, stainless steel, hemispherical contacts separated 1 cm edge-to-edge, oriented along the long axis of the forearm. The average transverse spacing between bipolar electrode pairs was 1.9 cm center-to-center. A reference electrode was gelled and secured on the ventral side of the forearm, just distal to the bipolar electrodes. Each bipolar EMD signal was differentially amplified (Liberating Technologies, Inc. BE328 amplifier; pass band from 30–500 Hz, CMRR > 100 dB over the pass band) and selectable gain applied. EMG were acquired at 2048 Hz using a 16-bit ADC.

As shown in Fig. 1, subjects sat and extended their dominant arm to place their hand in a thermo-formable plastic splint that was rigidly attached to a load cell (AMTI, Watertown, MA; model MC3A-100 transducer, Gen 5 signal conditioner). The metacarpal region of the hand was tightly secured to the splint using Velcro, while the phalanges were free. This attachment isolated measurement of forces at the wrist. The palm of the hand was perpendicular to the plane of the floor, the hand was in a neutral position with respect to the wrist, the elbow was extended and the upper arm was rotated ~45^o forward from the anatomical position. The arm was supported just distal to the olecranon process. The load cell measured three DoFs, which were displayed on a computer screen directly in front of the subject via an arrowhead cursor. Wrist extension-flexion (Ext-Flx) specified the *x*-axis location of the arrowhead, radial-ulnar deviation (Rad-Uln) the *y*-axis location and pronation-supination (Pro-Sup) moment the angular rotation. A second computer-generated target arrowhead could also be displayed. The three load cell signals were also sampled at 2048 Hz at 16-bit resolution.

MVCs and 50% MVCs were measured in each of wrist extension, flexion, radial and ulnar deviation, pronation and supination, along with a rest recording. These calibration contractions were used for force normalization, EMG noise assessment and calibration of advanced EMG processing techniques [20, 21]. Contractions for model training and testing followed. First, 1-DoF quasi-static trials were conducted separately for Ext-Flx, Rad-Uln and Pro-Sup. For Ext-Flx, subjects followed the computer screen force target as it took 30 s to linearly ramp from the force midpoint, to 30% MVC flexion, to 30% MVC extension, back to 30% MVC flexion and then back to the force range midpoint. Analogous ramp trajectories were used for Rad-Uln and Pro-Sup trials. Four trials per DoF were recorded (12 trials in total), randomized by DoF. During each trial, the on-screen arrowhead cursor that was controlled by the subject was only permitted to move along the active DoF. Second, 2-DoF quasi-static trials were conducted by eliciting ramp co-contraction of pairs of contraction directions. Two DoFs were active and their target effort levels were coincident. The same 30 s ramp trajectory was used. Two repetitions of six randomized trials were conducted (12 trials in total), the trials being identified by the contraction directions associated with the first 30% MVC co-contraction achieved. The subject-controlled arrowhead was only permitted to move/rotate along the two active DoFs. Third, 40-s duration, 1-DoF dynamic force trials were conducted separately for each of the three DoFs. For Ext-Flx, the target followed a random, uniform trajectory between 30% MVC extension and 30% MVC flexion, band-limited between 0–1 Hz. Three such trials were conducted for each DoF, randomized by DoF. The subject-controlled arrowhead was only permitted to move along the active DoF. Fourth, 40-s duration, 2-DoF dynamic force trials were conducted for each of the three pairs of DoFs. For these 2-DoF tasks, the target moved randomly and independently in each DoF. Three such trials were conducted for each DoF pair, randomized in order. All four sets of contractions were conducted at an interval of at least two minutes, to avoid accumulated fatigue. Subjects were released from the hand cuff between experiment stages.

For the second experimental session (contralateral trials), the apparatus differed only in that the electrodes were mounted on the contralateral forearm and that the contralateral arm was identically constrained with its hand secured to a second hand cuff (Fig. 2). Load cell measurement was still only provided for the dominant hand. MVC calibrations were not repeated; rather, the values from the first experimental session were used. Subjects completed the 50% MVC trials and the four sets of contractions for model training and testing (see previous paragraph). Subjects were provided load cell feedback from their dominant arm and instructed to mirror this effort level on their non-dominant (contralateral) side.

B. Methods of Analysis

Analysis was performed offline using MATLAB (The MathWorks, Inc., Natick, MA). Only causal algorithms were studied. EMG amplitude was estimated from each EMG signal. Each EMG signal was highpass filtered (5th-order Butterworth, cut-off at 15 Hz), notch filtered at the power-line frequency of 60 Hz (2nd-order notch filter, 1 Hz bandwidth) and rectified. Data from quasi-static trials were then lowpass filtered (cut-off frequency of 1.6 Hz; Chebyshev Type 1 filter, 9th-order, 0.05 dB peak-to-peak passband ripple) and downsampled to 4.096 Hz. Data from dynamic force trials were then lowpass filtered (cut-off frequency of 16 Hz; Chebyshev Type 1 filter, 9th-order, 0.05 dB peak-to-peak passband ripple) and downsampled to 40.96 Hz. Separately, the three mechanical signals were each normalized to their respective MVC value per DoF, and then similarly decimated depending on the trial type (to 4.096 Hz for quasi-static trials and to 40.96 Hz for dynamic trials). Hence, the input-output data sets available for EMG-force modeling were sampled at a rate that was approximately ten times the bandwidth of the output, which is appropriate for system identification [22, 23].

First, 1-DoF models were fit for each subject, using the *quasi-static* 1-DoF trials. For Ext-Flx, EMGs were least squares fit to Ext-Flx force (the remaining mechanical measures were ignored) via the model:

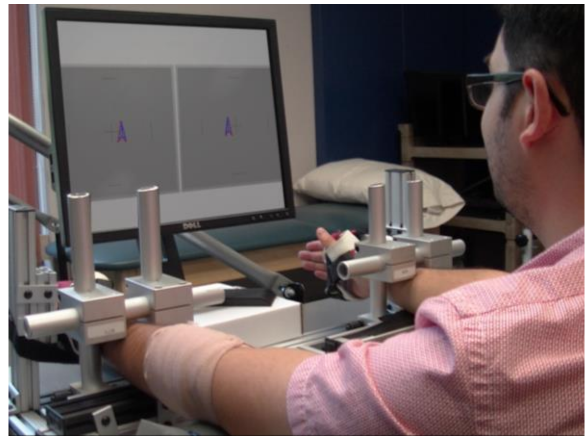

Fig. 2. **Contralateral** data collection apparatus. Both hands are constrained, but load cell measurements are only made from the dominant (right) side. Electrodes mounted about non-dominant (left) forearm.

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

where T_{E-F} was Ext-Flx force, *m* was the decimated discrete-time sample index, *E* was the number of electrodes (initially set to 16), $c_{e,q}$ were the fit coefficients and $\sigma_e[m-q]$ were the EMG amplitude values. Model order *Q* was set to 0, since the quasi-static trials had essentially no dynamics. Fit coefficients were determined using least squares via the pseudo-inverse technique, 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 of 0.01. This tolerance was selected after some initial evaluation over a range of tolerance values. Two quasi-static trials were used to train a model. Backward stepwise selection was then used to progressively reduce the number of EMG channels (i.e., omit the channel whose absence resulted in the lowest error), making all decisions only on the training trials. The two remaining 1-DoF trials were used for testing at each step (normalized RMS error in %MVC, averaged across the two trials). This process was repeated after exchanging the training and testing trials, for cross-validation. The average of the cross-validated results is reported. An identical process was then repeated for 1-DoF models relating EMG to Rad-Uln force and, separately, Pro-Sup moment.

Second, 2-DoF models were fit for each subject, using the *quasi-static* trials and the static model of (1). The EMG-force model and backward stepwise selection were applied identically, except that the model always simultaneously estimated two mechanical DoFs (the third, unused mechanical force/moment was ignored). Model training optionally consisted of 1-DoF trials (the first repetition of two trials from each relevant DoF), or 2-DoF trials (the first repetition of four trials, one per 2-DoF contraction direction), or both. For testing, RMS error was assessed separately for 1-DoF test trials and 2-DoFs trials, always for the two available mechanical dimensions. (During 1-DoF trials, the second mechanical dimension remained near zero throughout the trial.) The trial repetitions were switched and the overall error assigned as the average of the two-fold cross validation.

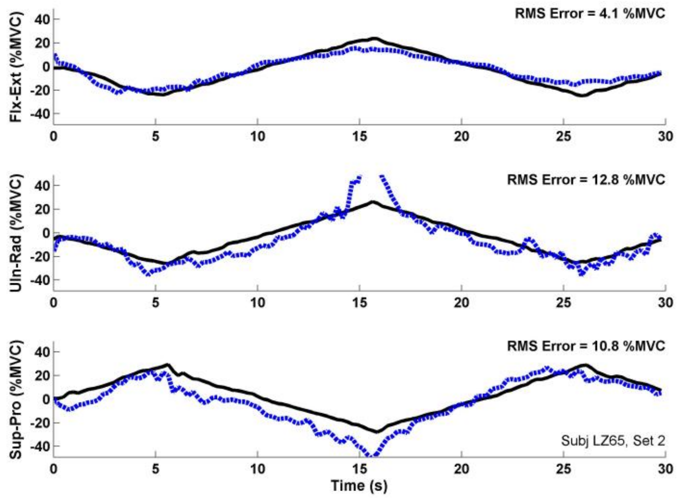

Fig. 3. **Contralateral, 1-DoF Model, Quasi-Static:** Example time-series plots of one-degree-of-freedom models, contralateral trials, quasi-static, two electrodes. Solid black lines are actual forces/moment, dashed blues lines are EMG-estimated.

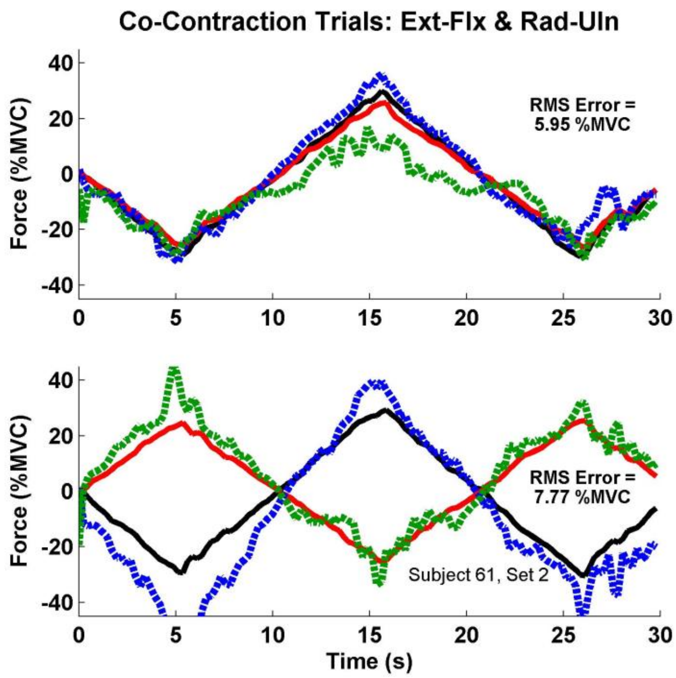

Fig. 4. **Contralateral, 2-DoF Model, Quasi-Static:** Example time-series plots of two-degree-of-freedom models. Contralateral trials, quasi-static, four electrodes. Training was from both 1- and 2-DoF trials. Key: solid black = actual Ext-Flx, dashed blue = estimated Ext-Flx, solid red = actual Rad-Uln, dash green = estimated Rad-Uln. Positive %MVC corresponds to Ext/Rad.

Third, 1-DoF models were fit for each subject, using the *dynamic* trials and the model of (1), with model order selected as $Q = 25$ [24]. For each DoF, three trials were available. Two were used for training and one for testing, with full cross-validation. The average cross-validated result is reported.

Fourth, 2-DoF models were fit for each subject, using the *dynamic* trials and model order $Q = 25$. For each pair of DoFs, three trials were available. Two were used for training and one for testing, with full cross-validation and the averaged result reported. As before, training from 1-DoF, 2-DoF or both trials was separately pursued.

TABLE I. **QUASI-STATIC TRIALS:** SUMMARY RESULTS (%MVC) OF BI-LATERAL MIRROR TRAINING COMPARISON OF IPSILATERAL VS. CONTRALATERAL EMG-FORCE ERRORS IN THREE SUBJECTS

Condition	Ipsi v. Contra	DoF(s)		
1-DoF Models (2 electrodes)		**Ext-Flx**	**Rad-Uln**	**Pro-Sup**
Assessed on 1-DoF trials	Ipsi: Contra:	5.1 ± 1.4 5.6 ± 2.0	7.1 ± 2.1 11.1 ± 9.5	8.5 ± 5.3 10.4 ± 3.3
2-DoF Models (4 electrodes)		**Ext-Flx & Rad-Uln**	**Ext-Flx & Pro-Sup**	**Rad-Uln & Pro-Sup**
Train with 1- DoF trials; Assess with 1-DoF trials	Ipsi: Contra:	5.5 ± 2.6 6.5 ± 3.8	6.7 ± 2.5 6.1 ± 2.1	7.3 ± 2.9 7.2 ± 4.7
Train with 1-DoF trials; Assess with 2-DoF trials	Ipsi: Contra:	9.6 ± 1.6 13.2 ± 6.6	13.2 ± 4.4 11.2 ± 2.4	17.5 ± 14.7 14.6 ± 2.5
Train with 1- and 2-DoF trials; Assess with 2-DoF trials	Ipsi: Contra:	6.8 ± 1.1 11.2 ± 7.4	8.5 ± 1.5 8.9 ± 2.2	9.6 ± 3.2 9.9 ± 4.7

Note that statistical comparisons will not be presented, as only three subjects participated in this study. Rather, trends will be noted in the EMG-force errors. In addition, direct comparison of the absolute error values between 1-DoF models and 2-DoF trials must be approached cautiously, since the underlying data differ.

III. RESULTS

Quasi-Static Models: Fig. 3 shows sample time-series test results of contralateral EMG-force for the 1-DoF models based on the quasi-static trials. Fig. 4 shows similar (contralateral) results for the 2-DoF models based on quasi-static trials and training from both 1- and 2-DoF trials. Table 1 shows summary quasi-static results for the three subjects, where we have concentrated on two-channel systems for the 1-DoF models and four-channel systems for the 2-DoF models. Table I shows that each 1-DoF model had average errors that were 10–56% higher for contralateral-trained models. If effect size is taken as the difference of the paired means divided by their average standard deviation, then it ranges from 0.29–0.69. When assessing on 2-DoF models, overall lower errors were achieved when training from both 1- and 2-DoF trials. And, these average performance differences were similar in percentage as to the 1-DoF models, with contralateral-trained models performing 3–65% poorer (effect size: 0.08–1.04).

Dynamic Models: Fig. 5 shows sample time-series test results of contralateral EMG-force for the 2-DoF models based on the dynamic trials. Fig. 6 shows dynamic model contralateral results as a function of the number of electrodes for 2-DoF models, when training was from only the 2-DoF trials. Results when training from only the 1-DoF trials or from both followed the same trends. For all three DoF pairs, average errors varied little as the number of electrodes was reduced from 16 down to 4. Further decreases in electrodes led to

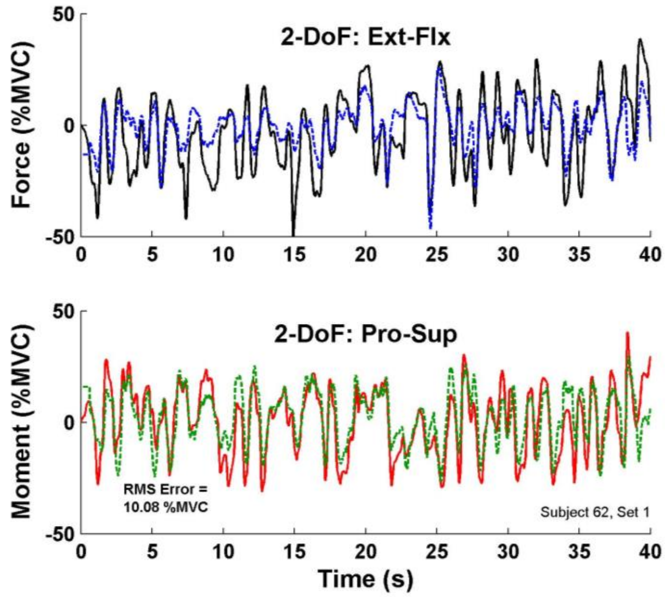

Fig. 5. **Contralateral, 2-DoF Model, Dynamic:** Example time-series plots of 2-DoF models, contralateral contractions, dynamic tracking with four electrodes. Key: solid black = actual Ext-Flx, dashed blue = estimated Ext-Flx, solid red = actual Pro-Sup, dashed green = estimated Pro-Sup. Training from both 1- and 2-DoF trials.

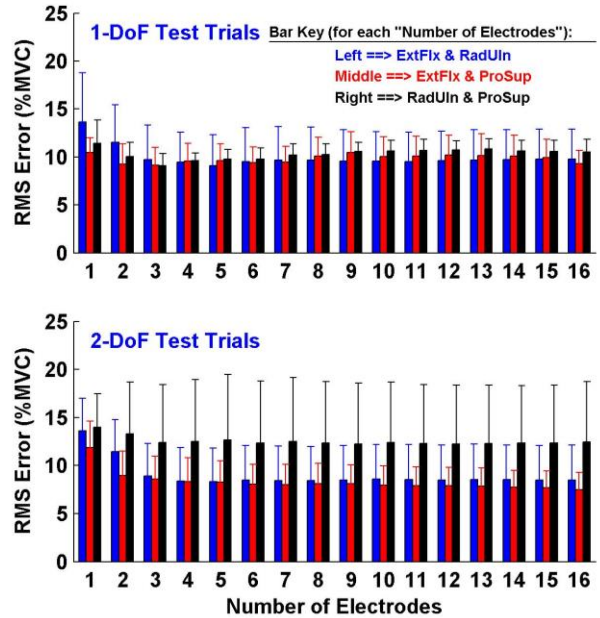

Fig. 6. **Contralateral, 2-DoF Model, Dynamic:** Comparison of (cross-validated) mean plus std. dev. results between contraction types for 2-DoF models vs. number of electrodes. Training from only 2-DoF trials.

progressive increases in the average error. For Rad-Uln & Pro-Sup, errors were always larger (compared to the other DoF pairs), particularly for 2-DoF assessment. Tables II and III show summary dynamic results for the three subjects. For 1-DoF models (Table II), contralateral-trained models performed better for Ext-Flx, but poorer for the two other DoFs. With two electrodes, the differences ranged from 6–19%. As the number of electrodes was increased, some limited error improvement seemed to result. For 1-DoF models (Table III), contralateral training errors using four electrodes were 9–18% higher, except when pairing Rad-Uln with Pro-Sup (errors were both higher and lower). Note that the Rad-Uln & Pro-Sup errors were larger than those of the other two pairings, thus this 2-DoF pairing would seem to be least valuable for use in prosthesis control. Again, as the number of electrodes was increased, there appeared to be some limited reduction in error.

IV. Discussion

Under both quasi-static and dynamic contractions, the majority of error comparisons found that when comparing ipsilateral vs. contralateral training, errors were greater (by 6–56 %MVC) when contralateral training was used. Note that this result does ***not*** imply that forces produced by the two arms of the subjects varied by 6–56%. In particular, if the force on one side was a constant fraction of that of the other, the *gains* of the EMG-force models would appropriately adjust to correct this error entirely. Further, dynamic models (i.e., those used to model the dynamic trials) can adjust for systematic *linear* differences between the left- and right-side forces, at least those consistent with the systems available in our model (25^{th}-order FIR filters). Hence, the differences in errors shown in Table I–III are most indicative of differences in contraction profiles (left- vs. right-side) and not absolute strength.

Accordingly, it would be interesting to simultaneously measure the forces produced by both arms, to better understand the ability of able-bodied subjects to match contralateral efforts. Regardless, subjects with limb absence likely have more difficulty in matching contralateral efforts than do able-bodied subjects, since limb-absent subjects also lack aspects of motor feedback (proprioception and force).

In summary, the trend in our results was for larger errors in contralateral-trained models than in ipsilateral-trained models. The average error differences in quasi-static 1-DoF trials varied from 6–56%, when measured in %MVC (effect size: 0.29–0.69). Differences were as large as 65% (effect size 1.04) in quasi-static 2-DoF trials (Ext-Flx & Rad-Uln). These results suggest that differences in contralateral contraction profiles account for some of the additional errors commonly found when training EMG-force models using bi-lateral mirrored contractions. Additional study in a larger able-bodied population is warranted, in which it would also be useful to simultaneously measure the forces produced by both wrists, providing a more complete comparison of the ability—and limitations—of subjects to match contraction profiles contralaterally. With the cases giving the better effect sizes of 1.04 and 0.69, this pilot study finds that, in a full study, paired comparisons at α=0.05 would require a sample size of 10 and 19, respectively, for 80% statistical power [25].

References

[1] P. Parker, K. Englehart, and B. Hudgins, "Myoelectric signal processing for control of powered limb prostheses," *J. Electromyo. Kinesiol.*, vol. 16, pp. 541–548, 2006.

[2] D. J. Atkins, D. C. Y. Heard, and W. H. Donovan, "Epidemilogic overview of individuals with upper-limb loss and their reported research priorities," *J. Prosthet. Orthot.*, vol. 8, pp. 2–11, 1996.

[3] T. A. Kuiken, G. A. Dumanian, R. D. Lipschutz, L. A. Miller, and K. A. Stubblefield, "The use of targeted muscle reinnervation for improved myoelectric prosthesis control in a bilateral shoulder disarticulation amputee," *Prosthet. Orthot. Int.*, vol. 28, pp. 245–253, 2005.

TABLE II

DYNAMIC TRIALS, 1-DOF MODELS: SUMMARY RESULTS (MEAN ± STD. DEV % MVC RMS ERROR). PARENTHESES IN FINAL COLUMN INDICATE NUMBER OF ELECTRODES CORRESPONDING TO MINIMUM AVERAGE ERROR.

Motion	Ipsilateral				Contralateral			
	2 Electrodes	4 Electrodes	8 Electrodes	Electrodes with Min. Error	2 Electrodes	4 Electrodes	8 Electrodes	Electrodes with Min. Error
Ext-Flx	5.5 ± 0.8	5.3 ± 1.5	5.2 ± 1.7	(9) 5.1 ± 1.7	5.2 ± 2.8	5.0 ± 2.6	4.8 ± 2.1	(14) 4.7 ± 2.0
Rad-Uln	7.0 ± 4.5	6.5 ± 4.2	5.9 ± 3.8	(9) 5.9 ± 3.7	8.3 ± 4.8	8.1 ± 4.7	7.9 ± 5.1	(7) 7.4 ± 4.2
Pro-Sup	6.3 ± 2.2	5.4 ± 1.9	5.5 ± 1.3	(6) 5.2 ± 1.5	6.7 ± 2.1	6.6 ± 2.4	6.6 ± 2.4	(3) 6.4 ± 2.4

TABLE III

DYNAMIC TRIALS, 2-DOF MODELS: SUMMARY RESULTS (MEAN ± STD. DEV % MVC RMS ERROR). PARENTHESES IN FINAL COLUMN INDICATE NUMBER OF ELECTRODES CORRESPONDING TO MINIMUM AVERAGE ERROR.

Motion	Ipsilateral			Contralateral		
	4 Electrodes	8 Electrodes	Electrodes with Min. Error	4 Electrodes	8 Electrodes	Electrodes with Min. Error
Train with 1-DoF Trials						
Ext-Flx&Rad-Uln	9.8 ± 3.4	9.2 ± 3.7	(5) 9.0 ± 3.4	11.2 ± 4.1	10.9 ± 3.6	(12) 10.7 ± 3.4
Ext-Flx&Pro-Sup	9.2 ± 1.1	8.9 ± 1.7	(10) 8.7 ± 1.8	10.4 ± 3.1	9.6 ± 2.8	(13) 9.4 ± 2.8
Rad-Uln&Pro-Sup	16.9 ± 7.4	16.8 ± 7.4	(16) 14.8 ± 5.9	11.8 ± 4.0	12.4 ± 3.6	(6) 11.7 ± 3.3
Train with 2-DoF Trials						
Ext-Flx&Rad-Uln	7.2 ± 2.6	6.8 ± 3.1	(14) 6.7 ± 3.0	8.4 ± 4.3	8.4 ± 4.4	(5) 8.3 ± 4.2
Ext-Flx&Pro-Sup	7.1 ± 1.5	6.6 ± 1.6	(10) 6.2 ± 0.7	8.3 ± 3.0	8.1 ± 2.6	(16) 7.5 ± 2.2
Rad-Uln&Pro-Sup	12.4 ± 7.3	11.7 ± 8.8	(12) 10.6 ± 7.8	12.5 ± 7.9	12.3 ± 7.8	(12) 12.3 ± 7.5
Train with 1- and 2-DoF Trials						
Ext-Flx&Rad-Uln	8.0 ± 2.9	7.4 ± 2.9	(12) 7.1 ± 3.1	9.4 ± 4.0	8.5 ± 3.8	(14) 8.4 ± 3.8
Ext-Flx&Pro-Sup	7.9 ± 0.7	7.0 ± 1.5	(16) 6.9 ± 1.5	8.6 ± 2.9	7.8 ± 2.2	(16) 7.7 ± 2.2
Rad-Uln&Pro-Sup	12.9 ± 7.6	11.4 ± 6.1	(15) 11.1 ± 6.8	11.3 ± 5.5	11.2 ± 5.5	(6) 11.1 ± 5.3

[4] T. A. Kuiken, G. Li, B. A. Lock, R. D. Lipschutz, L. A. Miller, K. A. Stubblefield, *et al.*, "Targeted muscle reinnervation for real-time myoelectric control of multifunction artificial arms," *J. Am. Med. Assoc.*, vol. 301, pp. 619–628, 2009.

[5] D. Graupe and W. K. Cline, "Functional separation of EMG signals via ARMA identification methods for prosthesis control purposes," *IEEE Trans. Sys. Man Cyber.,* vol. 5, pp. 252–259, 1975.

[6] B. Hudgins, P. Parker, and R. N. Scott, "A new strategy for multifunction myoelectric control," *IEEE Trans. Biomed. Eng.,* vol. 40, pp. 82–94, 1993.

[7] R. Boostani and M. H. Moradi, "Evaluation of the forearm EMG signal features for the control of a prosthetic hand," *Physiol. Meas.,* vol. 24, pp. 309–319, 2003.

[8] K. Englehart and B. Hudgins, "A robust, real-time control scheme for multifunction myoelectric control," *IEEE Trans. Biomed. Eng.,* vol. 50, pp. 848–854, 2003.

[9] M. A. Powell, R. R. Kaliki, and N. V. Thakor, "User training for pattern recognition-based myoelectric prostheses: Improving phantom limb movement consistency and distinguishability," *IEEE Trans. Neural Sys. Rehabil. Eng.,* vol. 22, pp. 522–532, 2014.

[10] P. Liu, D. R. Brown, E. A. Clancy, F. Martel, and D. Rancourt, "EMG-force estimation for multiple fingers," presented at the IEEE Sig. Proc. Med. Biol. Symp., 2013.

[11] S. Muceli and D. Farina, "Simultaneous and proportional estimation of hand kinematics from EMG during mirrored movements at multiple degrees-of-freedom," *IEEE Trans. Neural Sys. Rehabil. Eng.,* vol. 20, pp. 371–378, 2012.

[12] S. Muceli, N. Jiang, and D. Farina, "Extracting signals robust to electrode number and shift for online simultaneous and proportional myoelectric control by factorization algorithms," *IEEE Trans. Neural Sys. Rehabil. Eng.,* vol. 22, pp. 623–633, 2014.

[13] N. Jiang, K. B. Englehart, and P. A. Parker, "Extracting simultaneous and proportional neural control information for multiple-DOF prostheses from the surface electromyographic signal," *IEEE Trans. Biomed. Eng.,* vol. 56, pp. 1070–1080, 2009.

[14] N. Jiang, J. L. Vest-Nielsen, S. Muceli, and D. Farina, "EMG-based simultaneous and proportional estimation of wrist/hand kinematics in uni-lateral trans-radial amputees," *J. NeuroEng. Rehabil.,* vol. 9:42, 2012.

[15] A. Ameri, E. N. Kamavuako, E. J. Scheme, K. B. Englehart, and P. Parker, "Support vector regression for improved real-time, simultaneous myoelectric control," *IEEE Trans. Neural Sys. Rehabil. Eng.,* vol. 22, pp. 1198–1209, 2014.

[16] A. Fougner, O. Stavdahl, P. J. Kyberd, Y. G. Losier, and P. A. Parker, "Control of upper limb prosthesis: Terminology and proportional myoelectric Control—A review," *IEEE Trans. Neural Sys. Rehabil. Eng.,* vol. 20, pp. 663–677, 2012.

[17] J. L. Nielsen, S. Holmgaard, N. Jiang, K. B. Englehart, D. Farina, and P. Parker, "Simultaneous and proportional force estimation for multifunction myoelectric prostheses using mirrored bilateral training," *IEEE Trans. Biomed. Eng.,* vol. 58, pp. 681–688, 2011.

[18] A. Ameri, E. J. Scheme, E. N. Kamavuako, K. B. Englehart, and P. A. Parker, "Real-time, simultaneous myoelectric control using force and position-based training paradigms," *IEEE Trans. Biomed. Eng.,* vol. 61, pp. 279–287, 2014.

[19] H. J. M., F. Biebmann, N. Jiang, H. Rehbaum, D. Farina, F. C. Meinecke, *et al.*, "Linear and nonlinear regression techniques for simultaneous and proportional myoelectric control," *IEEE Trans. Neural Sys. Rehabil. Eng.,* vol. 22, pp. 269–279, 2014.

[20] E. A. Clancy and K. A. Farry, "Adaptive whitening of the electromyogram to improve amplitude estimation," *IEEE Trans. Biomed. Eng.,* vol. 47, pp. 709–719, 2002.

[21] P. Prakash, C. A. Salini, J. A. Tranquilli, D. R. Brown, and E. A. Clancy, "Adaptive whitening in electromyogram amplitude estimation for epoch-based applications," *IEEE Trans. Biomed. Eng.,* vol. 52, pp. 331–334, 2005.

[22] E. A. Clancy, O. Bida, and D. Rancourt, "Influence of advanced electromyogram (EMG) amplitude processors on EMG-to-torque estimation during constant-posture, force-varying contractions," *J. Biomech.,* vol. 39, pp. 2690–2698, 2006.

[23] L. Ljung, *System Identification: Theory for the User*. Upper Saddle River, NJ: Prentice-Hall, 1999, pp. 491–519.

[24] E. A. Clancy, L. Liu, P. Liu, and D. V. Moyer, "Identification of constant-posture EMG-torque relationship about the elbow using nonlinear dynamic models," *IEEE Trans. Biomed. Eng.,* vol. 59, pp. 205–212, 2012.

[25] G. W. Snedecor and W. G. Cochran, *Statistical Methods*, 7th ed., Iowa State, 1980, p. 104.

A Pilot Study Assessing Ipsilateral vs. Contralateral Feedback in EMG-Force Models of the Wrist for Upper-Limb Prosthesis Control

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Introduction

❖Motivation

- Application: EMG control of upper-limb prosthetics
- Existing commercial control is only one degree of freedom
- Desire proportional, simultaneous and independent control of two degrees of freedom (2-DoF)

❖Problem

- Typically require "supervised" algorithm development
- But, unilateral limb-absent subjects cannot produce forces/movements on affected side

❖Solutions

- Ipsilateral Training: Train prosthesis using EMG from affected side, related to screen target
- Contralateral Training (Mirrored Bilateral): Train prosthesis using EMG from affected side, related to forces from able-bodied side
- We compared approaches in able-bodied pilot study (*N*=3)

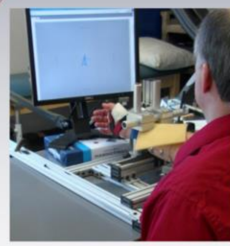

Fig. 1. Ipsilateral data collection apparatus

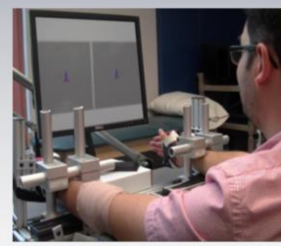

Fig. 2. Contralateral data collection apparatus

Methods

❖Experimental Data/Data Collection

- Three right-handed male subjects (aged 25, 37 and 53 years)
- 16 bipolar electrodes about proximal forearm (one arm)
- Both hands cuffed. Only right hand in load cell.
- Experimental procedures
  - Measure maximum force in right (dominant) arm
    - 3 different DoFs: Ext-Flx, Rad-Uln and Pro-Sup
  - Slow force varying ramp target trial (quasi-static)
    - 30% flexion to 30% extension to 30% flexion
    - One DoF trials
    - Two DoFs trials (3 possible combinations), co-contractions
  - Dynamic random target trial (0.75 Hz bandwidth, uniform random)
    - One DoF trials
    - Two DoFs trials (3 possible combinations)
- Two training styles: ipsilateral, contralateral
  - Fig. 1. Ipsilateral data collection apparatus
    - Dominant (right) hand tightly secured
    - 16 electrodes (not visible) secured about right arm
    - NO force feedback. Effort of right arm follows screen target.
  - Fig. 2. Contralateral data collection apparatus
    - Both hands constrained; load cell measurements only made from the dominant (right) side.
    - 16 electrodes (not visible) secured about non-dominant (left) forearm
    - Force feedback provided from right (dominant) arm
    - Non-dominant arm attempts to match effort of contralateral arm

❖Methods of Analysis

- EMG Processing (after sampling at 2048 Hz)
  - Highpass filter (5th Butterworth, cut-off at 15 Hz)
  - Notch filter (2nd notch filter, 1 Hz bandwidth at 60 Hz)
  - Rectify
  - Lowpass filter
    - 9th–order Chebyshev Type 1 filter at 1.6 Hz for Quasi-static
    - 9th–order Chebyshev Type 1 filter at 16 Hz for Dynamic
  - Downsample
    - 500:1 for Quasi-static (4.096 Hz); 50:1 for Dynamic (40.96 Hz)
- Model for system identification

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

  - T_{E-F}: Ext-Flx force (or Rad-Uln or Pro-Sup)
  - m: Decimated discrete time sample index
  - E: Number of electrodes (initially set to 16)
  - Q: Number of time lags
  - $c_{e,q}$: Fit coefficients
  - σ_e: EMG amplitude

- Modeling Methods
  - Quasi-static trials ➔Q=0; Dynamic trials ➔ Q=25
  - Least squares estimation of coefficients $c_{e,q}$
  - Reduce number of electrodes via backwards stepwise selection
  - 1 Degree of Freedom (DoF) models
    - Trained, tested on 1 DoF data
  - 2 Degree of Freedom (DoF) models
    - Trained on 1/2/1&2 DoF data; tested on 1- /2-DoF data
- Data collected on two days (6 month interval)
  - Day 1: Ipsilateral trials
  - Day 2: Contralateral trials
  - Comparison measure: normalized RMS error

- Limitations of the pilot study
  - Small amount of data (three subjects)
    - Thus, no statistical comparison presented

Results

- Tables I–III show general results of all test trials, averaged across the three subjects
- Figs. 3 & 4 show example testing results comparing estimated to measured forces, ***quasi-static*** trials
- Figs. 5 & 6 show example and summary results comparing estimated to measured forces, ***dynamic*** trials

TABLE I. **QUASI-STATIC TRIALS:** SUMMARY RESULTS (%MVC) OF BI-LATERAL MIRROR TRAINING COMPARISON OF IPSILATERAL VS. CONTRALATERAL EMG-FORCE ERRORS IN THREE SUBJECTS

Condition	Ipsi v. Contra	DoF(s)		
1-DoF Models (2 electrodes)		**Ext-Flx**	**Rad-Uln**	**Pro-Sup**
Assessed on 1-DoF trials	Ipsi: Contra:	5.1 ± 1.4 5.6 ± 2.0	7.1 ± 2.1 11.1 ± 9.5	8.5 ± 5.3 10.4 ± 3.3
2-DoF Models (4 electrodes)		**Ext-Flx & Rad-Uln**	**Ext-Flx & Pro-Sup**	**Rad-Uln & Pro-Sup**
Train with 1- DoF trials; Assess with 1-DoF trials	Ipsi: Contra:	5.5 ± 2.6 6.5 ± 3.8	6.7 ± 2.5 6.1 ± 2.1	7.3 ± 2.9 7.2 ± 4.7
Train with 1-DoF trials; Assess with 2-DoF trials	Ipsi: Contra:	9.6 ± 1.6 13.2 ± 6.6	13.2 ± 4.4 11.2 ± 2.4	17.5 ± 14.7 14.6 ± 2.5
Train with 1- and 2-DoF trials; Assess with 2-DoF trials	Ipsi: Contra:	6.8 ± 1.1 11.2 ± 7.4	8.5 ± 1.5 8.9 ± 2.2	9.6 ± 3.2 9.9 ± 4.7

TABLE II
DYNAMIC TRIALS, 1-DOF MODELS: SUMMARY RESULTS (MEAN ± STD. DEV % MVC RMS ERROR). PARENTHESES IN FINAL COLUMN INDICATE NUMBER OF ELECTRODES CORRESPONDING TO MINIMUM AVERAGE ERROR.

Motion	Ipsilateral				Contralateral			
	2 Electrodes	4 Electrodes	8 Electrodes	Electrodes with Min. Error	2 Electrodes	4 Electrodes	8 Electrodes	Electrodes with Min. Error
Ext-Flx	5.5 ± 0.8	5.3 ± 1.5	5.2 ± 1.7	(9) 5.1 ± 1.7	5.2 ± 2.8	5.0 ± 2.6	4.8 ± 2.1	(14) 4.7 ± 2.0
Rad-Uln	7.0 ± 4.5	6.5 ± 4.2	5.9 ± 3.8	(9) 5.9 ± 3.7	8.3 ± 4.8	8.1 ± 4.7	7.9 ± 5.1	(7) 7.4 ± 4.2
Pro-Sup	6.3 ± 2.2	5.4 ± 1.9	5.5 ± 1.3	(6) 5.2 ± 1.5	6.7 ± 2.1	6.6 ± 2.4	6.6 ± 2.4	(3) 6.4 ± 2.4

TABLE III
DYNAMIC TRIALS, 2-DOF MODELS: SUMMARY RESULTS (MEAN ± STD. DEV % MVC RMS ERROR). PARENTHESES IN FINAL COLUMN INDICATE NUMBER OF ELECTRODES CORRESPONDING TO MINIMUM AVERAGE ERROR.

Motion	Ipsilateral			Contralateral		
	4 Electrodes	8 Electrodes	Electrodes with Min. Error	4 Electrodes	8 Electrodes	Electrodes with Min. Error
Train with 1-DoF Trials						
Ext-Flx&Rad-Uln	9.8 ± 3.4	9.2 ± 3.7	(5) 9.0 ± 3.4	11.2 ± 4.1	10.9 ± 3.6	(12) 10.7 ± 3.4
Ext-Flx&Pro-Sup	9.2 ± 1.1	8.9 ± 1.7	(10) 8.7 ± 1.8	10.4 ± 3.1	9.6 ± 2.8	(13) 9.4 ± 2.8
Rad-Uln&Pro-Sup	16.9 ± 7.4	16.8 ± 7.4	(16) 14.8 ± 5.9	11.8 ± 4.0	12.4 ± 3.6	(6) 11.7 ± 3.3
Train with 2-DoF Trials						
Ext-Flx&Rad-Uln	7.2 ± 2.6	6.8 ± 3.1	(14) 6.7 ± 3.0	8.4 ± 4.3	8.4 ± 4.4	(5) 8.3 ± 4.2
Ext-Flx&Pro-Sup	7.1 ± 1.5	6.6 ± 1.6	(10) 6.2 ± 0.7	8.3 ± 3.0	8.1 ± 2.6	(16) 7.5 ± 2.2
Rad-Uln&Pro-Sup	12.4 ± 7.3	11.7 ± 8.8	(12) 10.6 ± 7.8	12.5 ± 7.9	12.3 ± 7.8	(12) 12.3 ± 7.5
Train with 1- and 2-DoF Trials						
Ext-Flx&Rad-Uln	8.0 ± 2.9	7.4 ± 2.9	(12) 7.1 ± 3.1	9.4 ± 4.0	8.5 ± 3.8	(14) 8.4 ± 3.8
Ext-Flx&Pro-Sup	7.9 ± 0.7	7.0 ± 1.5	(16) 6.9 ± 1.5	8.6 ± 2.9	7.8 ± 2.2	(16) 7.7 ± 2.2
Rad-Uln&Pro-Sup	12.9 ± 7.6	11.4 ± 6.1	(15) 11.1 ± 6.8	11.3 ± 5.5	11.2 ± 5.5	(6) 11.1 ± 5.3

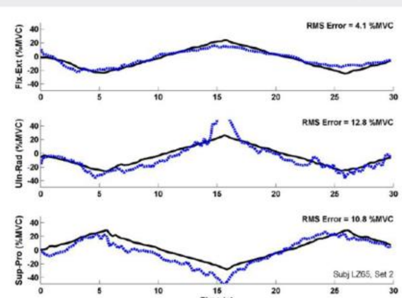

Fig. 3. **Contralateral, 1-DoF Model, Quasi-Static:** Example time-series plots of one-degree-of-freedom models, contralateral trials, quasi-static, two electrodes. Solid black lines are actual forces/moment, dashed blues lines are EMG-estimated.

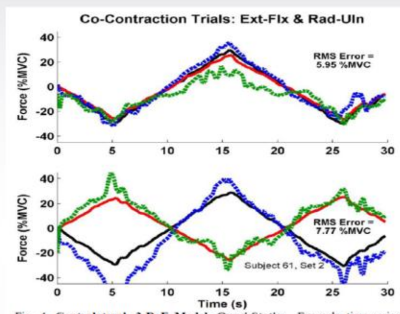

Fig. 4. **Contralateral, 2-DoF Model, Quasi-Static:** Example time-series plots of two-degree-of-freedom models. Contralateral trials, quasi-static, four electrodes. Training was from both 1- and 2-DoF trials. Key: solid black = actual Ext-Flx, dashed blue = estimated Ext-Flx, solid red = actual Rad-Uln, dash green = estimated Rad-Uln. Positive %MVC corresponds to Ext/Rad.

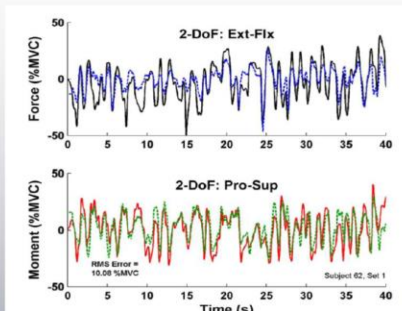

Fig. 5. **Contralateral, 2-DoF Model, Dynamic:** Example time-series plots of 2-DoF models, contralateral contractions, dynamic tracking with four electrodes. Key: solid black = actual Ext-Flx, dashed blue = estimated Ext-Flx, solid red = actual Pro-Sup, dashed green = estimated Pro-Sup. Training from both 1- and 2-DoF trials.

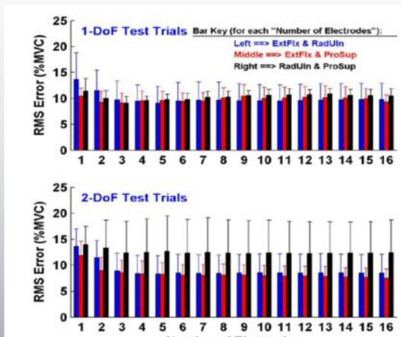

Fig. 6. **Contralateral, 2-DoF Model, Dynamic:** Comparison of (cross-validated) mean plus std. dev. results between contraction types for 2-DoF models vs. number of electrodes. Training from only 2-DoF trials.

Summary/Conclusion

The trend in our results was for larger errors in contralateral-trained models than in ipsilateral-trained models. The average error differences varied from 6–56%, when measured in %MVC. These results suggest that differences in contralateral contraction profiles account for some of the additional errors commonly found when training EMG-force models using bi-lateral mirrored contractions. Additional study in a larger able-bodied population is warranted, in which it would also be useful to simultaneously measure the forces produced by both wrists, providing a more complete comparison of the ability—and limitations—of subjects to match contraction profiles contralaterally.