



Two degrees of freedom, dynamic, hand-wrist EMG-force using a minimum number of electrodes

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ABSTRACT

Few studies have related the surface electromyogram (EMG) of forearm muscles to two degree of freedom (DoF) hand-wrist forces; ones that have, used large high-density electrode arrays that are impractical for most applied biomechanics research. Hence, we researched EMG-force in two DoFs—hand open-close paired with one wrist DoF—using as few as four conventional electrodes, comparing equidistant placement about the forearm to optimized site selection. Nine subjects produced 1-DoF and 2-DoF uniformly distributed random forces (band-limited to 0.75 Hz) up to 30% maximum voluntary contraction (MVC). EMG standard deviation (EMGo) was related to force offline using linear dynamic regression models. For 1-DoF forces, average RMS errors using two optimally-sited electrodes ranged from 8.3 to 9.0 %MVC, depending on the DoF. For 2-DoFs, overall performance was best when training from both 1- and 2-DoF trials, giving average RMS errors using four optimally-sited electrodes of 9.2 %MVC for each DoF pair (hand open-close paired with one wrist DoF). For each model, additional optimally-sited electrodes showed little statistical improvement. Electrodes placed equidistant performed noticeably poorer than an equal number of electrodes that were optimally sited. The results suggest that reliable 2-DoF hand-wrist EMG-force with a small number of electrodes may be feasible.

1. Introduction

Since the research of Inman et al. (1952) in 1952, a plethora of studies—utilizing a variety of modeling methods—have related surface electromyogram (EMG) activity to force/torque generated about a joint (Buchanan et al., 2004, Staudenmann et al., 2010). Various strategies have emerged to improve the fidelity of the EMG-force relationship, including: techniques to reduce the variability of the processed EMG (Clancy and Hogan, 1994, 1995, Hashemi et al., 2015, Hogan and Mann, 1980a, b, Parker et al., 2006, Potvin and Brown, 2004, Sanger, 2007), modeling agonist and antagonist muscles about a joint (An et al., 1983, Clancy and Hogan, 1997, Messier et al., 1971, Solomonow et al., 1986), applying system identification methods that adapt to each subject (Dai et al., 2017, Hasan and Enoka, 1985, Hashemi et al., 2012, Thelen et al., 1994), incorporating dynamic changes in force (Gottlieb and Agarwal, 1971; Hashemi et al., 2015, 2012), and considering variations in joint angle (Doheny et al., 2008, Hashemi et al., 2013, Hof and Van den Berg, 1981, Liu et al., 2015, Liu et al., 2013b). These

models have been utilized in numerous application areas, such as ergonomics assessment (Hagg et al., 2004, Kumar and Mital, 1996), clinical biomechanics (Disselhorst-Klug et al., 2009, Doorenbosch and Harlaar, 2003) and motor control research (Ostry and Feldman, 2003).

The vast majority of this research, particularly when applied to the upper limbs, has been limited to EMG-force (and EMG-kinematics) models of a single joint, typically utilizing one electrode placed over each large muscle. However, most skilled manipulation tasks require concurrent force generation at the hand and wrist—even simple opening of a door or use of a screwdriver requires hand grip with simultaneous wrist rotation. The primary muscles for both hand and wrist activation are smaller in size and adjacently located within the forearm. Some early EMG-based laboratory studies of multi-DoF hand and/or wrist contraction utilized high density electrode arrays with upwards of 32–64 (or more) electrodes. Such arrays were shown to extract more information and decrease the error in EMG-force/kinematics estimation (Hahne et al., 2014, Hwang et al., 2014, Liu et al., 2013a, Muceli and Farina, 2012, Muceli et al., 2014), but they are

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neither affordable nor practical for most applied biomechanics studies.

Emerging studies have explored EMG-based multiple DoF EMG-force/kinematics using 7–8 conventional electrodes, equally-spaced transversely about the forearm (Ameri et al., 2014, Amsuess et al., 2016, Jiang et al., 2009, Jiang et al., 2012, Nielsen et al., 2011), and Fougner et al. have placed 5 electrodes over anatomically-selected locations (Fougner et al., 2014). In a prior study (Clancy et al., 2017), we related forearm EMG to quasi-static 2-DoF forces at the wrist (without considering hand forces). Thus, none of these works has explored the influence or feasibility of reducing the quantity of conventional EMG channels to its minimum number during dynamic hand-wrist contractions [i.e., hand open-close (Opn-Cls) combined with one wrist DoF], nor the method for electrode site selection (Cavanaugh et al., 1983; Clancy et al., 2017) when doing so. Limiting the number of EMG electrodes is an important attribute in many applied biomechanics studies. In addition, when more electrodes are used in a preparation, the odds of a failure increase, with a single failing electrode channel potentially degrading the entire system (Clancy and Hogan, 1995).

Hence, we researched offline estimation of 2-DoF EMG-force—hand Opn-Cls in conjunction with one wrist DoF—using as few conventional electrodes as possible during *dynamic* (force-varying) *hand-wrist* contraction. In particular, each 2-DoF contraction trial, which produced random forces queued by a computer-generated target, incorporated hand Opn-Cls force with one of either wrist extension-flexion (Ext-Flx), radial-ulnar deviation (Rad-Uln) or pronation-supination (Pro-Sup). Electrode sites were either pre-determined or optimally located based on calibration contractions. Our results show that 2-DoF EMG-force had similar error levels when compared to 1-DoF EMG-force and required as few as 4–6 electrodes; but only if these electrode sites were optimally selected (i.e., via calibration contractions).

2. Methods

2.1. Data collection setup

After providing written informed consent (supervised by New England IRB; Protocol 14-408), experimental data from nine subjects (five males, four females; aged 27 ± 9.7 years) were acquired. Subjects sat at the experimental apparatus. The back of the dominant hand was tightly cuffed to a six-DoF load cell (MC3A-100 transducer, Gen 5 signal conditioner; AMTI, Watertown, MA) using a thermo-formable plastic mold, to measure force/torque generated at the wrist. A single-axis load cell (LCR-150, DMD-465WB amplifier; Omega Engineering, Inc., Stamford, CT) was secured around the distal thumb via a rigid tube and, separately on the opposing side of the cell, Velcro-secured to the proximal aspects of the four fingers to measure grip force during attempted hand Opn-Cls (Fig. 1). The palm of the hand was perpendicular with the plane of the floor, the wrist was relaxed in a neutral position with respect to the hand and the shoulder was flexed 45° forward from the anatomical position along the sagittal plane. The elbow was supported just distal to the olecranon process. The skin surface about the forearm was scrubbed with an alcohol wipe and electrode gel was applied. Sixteen bipolar EMG electrodes were secured equidistant in a row, circumferentially about the forearm (one electrode aligned with the most ulnar aspect; Fig. 2) with the mid-point between bipolar contacts situated 5 cm distal to the elbow crease. 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. A reference electrode was gelled and secured just proximal to the row of active electrodes. Each bipolar EMG signal was wired to a differential amplifier circuit (Liberating Technologies, Inc. BE328 amplifier; 30–500 Hz fourth-order pass band, CMRR > 100 dB over the pass band) and selectable gain was applied. As a measure of EMG system noise, the average ratio of resting RMS EMG to the RMS EMG at 50% maximum voluntary contraction (MVC) was $8.1 \pm 5.4\%$ (median of 7.2%). A real-time feedback signal from the load cells was shown via a

blue arrowhead on the computer screen (Fig. 3) in front of the subject. The arrowhead could display each DoF—*x*-axis location for Ext-Flx force, *y*-axis location for Rad-Uln force, rotation for Pro-Sup moment, and size for hand Opn-Cls. A second red dashed-line arrowhead displayed a computer-controlled target that guided the subject to complete different experimental tasks. Four load cell signals and 16 EMG channels were each sampled at 2048 Hz with 16-bit resolution.

2.2. Data collection contractions

All contractions were constant-posture. A minimum two-minute rest interval was provided between contractions to prevent muscle fatigue. After a warm-up period, MVC was measured once and separately for both directions (e.g., open vs. close) for each of the four DoFs. A subject took 2–3 s to ramp up their effort to MVC, maintaining that effort for two seconds. The plateau level of this force/moment was the MVC. Lastly, rest trials were recorded for noise level evaluation.

Next, subjects proceeded to 1-DoF dynamic tracking trials. Each of the four DoFs was tested separately. Subject feedback only modified the arrowhead according to changes in the specified DoF. For Ext-Flx, the target arrowhead generated a random target moving between $\pm (|30\% \text{ MVC Flx}| + |30\% \text{ MVC Ext}|)/2$ on the *x*-axis of the screen, and subjects were asked to track the movement of the target. The random target was a 0.75 Hz band-limited, white and uniform random process. Preliminary testing was used to select this bandwidth as the widest in which subjects could maintain target tracking for these tasks. Note that this bandwidth is narrower than our past 1-DoF studies at the elbow (Dai et al., 2017), likely reflecting the more challenging task of 2-DoF target tracking using two joints. Four trials of 40 s duration each were collected. The equivalent experiment was applied for the three remaining DoFs (16 total trials); except that the force maximum was reduced to 15 %MVC for Opn-Cls due to excessive fatigue experienced in preliminary testing (particularly during hand open). The order of presentation of the DoFs was randomized.

Lastly, 2-DoF trials were conducted in which two different DoFs were tracked simultaneously. We only considered three combinations: hand Opn-Cls combined with one of the three wrist DOFs (Ext-Flx, Rad-Uln or Pro-Sup). The same random target style was used, but with two independent random instances (one per DoF). Four trials of 40 s duration were collected for each hand-wrist combination (12 total trials).

2.3. Methods of analysis—pre-processing

Data analysis was performed offline in MATLAB (The MathWorks, Inc., Natick, MA). All filters were implemented in the forward and reverse time directions to achieve a noncausal, zero-phase and magnitude squared response. An estimate of EMG standard deviation (EMG σ) was computed for each EMG channel as follows: raw EMG were highpass filtered to further reduce motion artifact (fifth-order Butterworth, cut-off at 15 Hz), notch filtered to attenuate power-line interference with little loss of signal power (second-order IIR filter at 60 Hz, notch bandwidth of 1 Hz), rectified, lowpass filtered (16 Hz cut-off, Chebyshev Type 1 filter, ninth-order, 0.05 dB peak-to-peak passband ripple), and then down-sampled from 2048 Hz to 40.96 Hz. This resulting frequency is suitable for system identification of EMG-force dynamic models (Clancy et al., 2006, Ljung, 1999). The lowpass filter can be regarded as an initial smoothing window for the EMG σ estimate, with additional smoothing—optimized to each subject, but typically with a lowpass cut-off frequency at or below 1 Hz (Koirala et al., 2015)—produced by the dynamic EMG-force model described below. Each force/moment signal (Opn-Cls, Ext-Flx, Rad-Uln and Pro-Sup) was normalized by its corresponding MVC level pair. For example, Ext-Flx was normalized by: $(|MVC_{Ext}| + |MVC_{Flx}|)/2$.

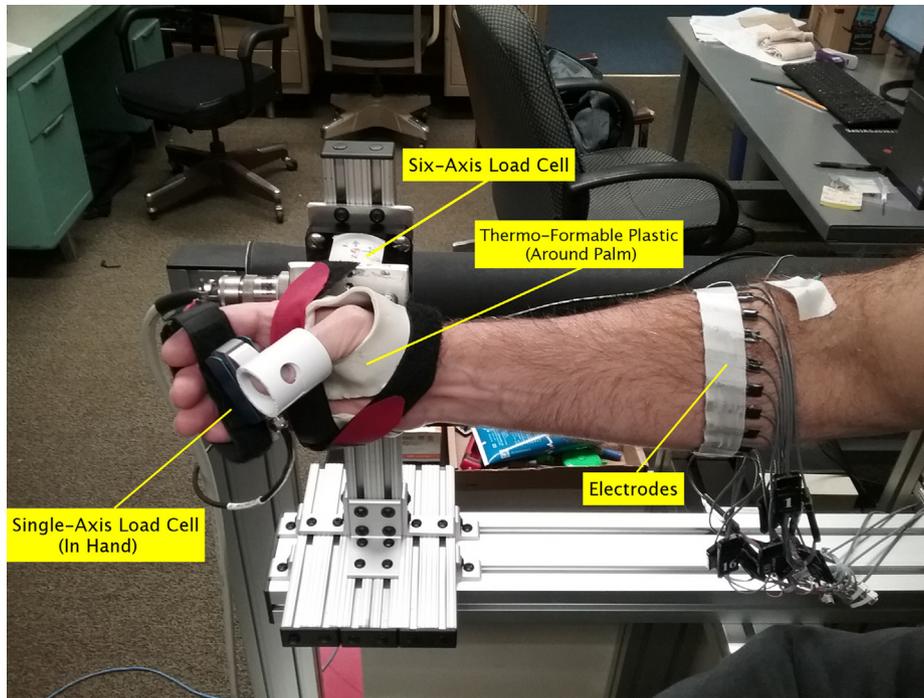


Fig. 1. Experimental apparatus. Dominant hand was tightly secured via thermo-formable plastic and Velcro to six-axis load cell. Fingers were secured to a single-axis load cell (thumb on one side, remaining four on the other). Sixteen electrodes were secured about the dominant forearm.

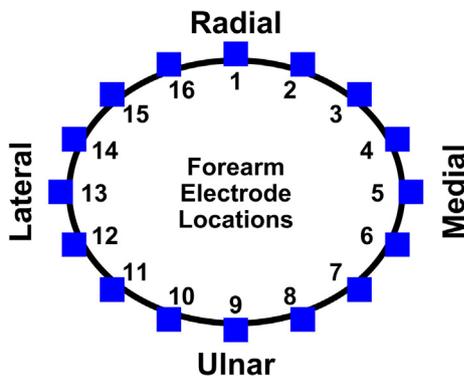


Fig. 2. Transverse view of forearm showing electrode locations. Blue squares depict electrode locations about the circumference of the forearm relative to the medial, lateral, radial and ulnar aspects. Numbers list the electrode associated with each location. (For interpretation of the references to colour in this figure legend, the reader is referred to the web version of this article.)

2.4. Methods of analysis—One-DoF dynamic models

The processed extension and flexion EMG values were related to Ext-Flx wrist force via a 1-DoF linear dynamic model as:

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

where T_{E-F} was wrist Ext-Flx force, m was the decimated discrete-time sample index, Q was the order of the linear dynamic model (set to 20 based on prior study (Clancy et al., 2012) and preliminary evaluation of these data), E was the number of electrodes used in the fit (initially set to 16), and $c_{e,q}$ were the fit coefficients. A linear model was chosen in this initial study to limit the total number of free parameters and, thus, reduce the risk of overfitting (Ljung, 1999). Two of four trials were used for coefficient training, using the known EMG values and force. The linear least squares pseudo-inverse method (Press et al., 1994) was performed for model training, in which singular values of the design

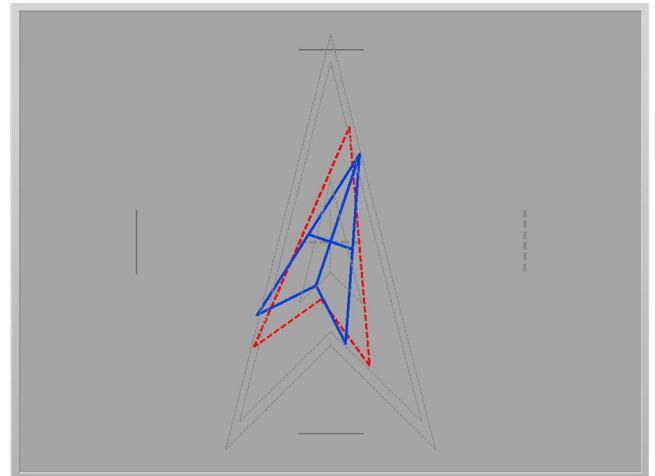


Fig. 3. Feedback screen shown to subject. Dashed red arrowhead is computer-controlled target, solid blue arrowhead is subject force/moment. (Additional permanent gray arrows and lines were used as fixed targets during calibration tasks.) Each arrowhead displayed four different DoFs— x -axis location for Ext-Flx force, y -axis location for Rad-Uln force, rotation for Pro-Sup moment, and size for hand Opn-Cls. (For interpretation of the references to colour in this figure legend, the reader is referred to the web version of this article.)

matrix were removed if the ratio of that singular value to the largest was less than a tolerance value, Tol (set to 0.01 based on prior study (Clancy et al., 2012) and preliminary evaluation of these data). The remaining two trials were used for testing (RMS error between the estimated and measured torques). The training and testing sets were flipped for two-fold cross-validation, and the average of these two results reported. Two-fold cross validation was selected for computational efficiency, and because the remaining four folds would necessarily yield correlated results (which are statistically less efficient). Since the mechanical signals were normalized by MVC, the final RMS error was in % MVC.

For pre-determined electrode sites, either 2, 4, 8 or 16 electrodes

were utilized. For Flx-Ext, the 2-electrode model used the most medial and lateral electrodes (electrodes 5 and 13 in Fig. 2). The 4-electrode model added electrodes half way in-between (electrodes 1, 5, 9 and 13 in Fig. 2). The 8-electrode model added four more electrodes, each half way between the prior four (electrodes 1, 3, 5, 7, 9, 11, 13 and 15 in Fig. 2). For calibration-based selection of electrode sites, backward stepwise selection was utilized. All 16 EMG channels were entered initially. Then, the channel whose absence resulted in the lowest RMS error was excluded for each step. Stepping continued until only one electrode remained. Identical modeling was separately performed for the other three DoFs (Opn-Cls, Rad-Uln and Pro-Sup). Opn-Cls and Pro-Sup used the same 2-electrode model as Flx-Ext, while Rad-Uln used the electrodes at the most radial and ulnar aspects of the forearm (electrodes 1 and 9 in Fig. 2).

2.5. Methods of analysis—Two-DoF dynamic models

Similar 2-DoF EMG-force models were evaluated (for pre-determined electrode sites and backward stepwise site selection, again using two-fold cross-validation) for each of the three pairs of dimensions tested (Opn-Cls paired with one wrist DoF). These models estimated two DoFs simultaneously, using separate fit coefficients for each DoF. Thus, each EMG channel contributed to each DoF. All six combinations of three different training paradigms and two testing paradigms were performed to evaluate the best modeling strategy. The training paradigms were: training with 1-DoF trials, with 2-DoF trials, or with both 1- and 2-DoF trials. The testing paradigms were: testing on 1-DoF trials or on 2-DoF trials. When testing on 1-DoF trials for these 2-DoF models, the non-used dimension would be expected to remain near a zero value throughout the trial. These 1-DoF tests were intended to determine if 2-DoF models could still perform well when encountering 1-DoF tasks. For pre-determined electrode sites, 4-, 8- and 16-electrode models were studied. The initial four electrodes were always at the most medial and lateral locations, and at the most radial and ulnar aspects of the forearm (electrodes 1, 5, 9 and 13 in Fig. 2).

2.6. Methods of analysis—statistics

Performance differences were tested statistically with SPSS 22 using multivariate repeated measures analysis of variance (RANOVA), assessing all possible interactions. These interactions were not significant, unless noted otherwise. Normality of the residuals was tested for each of the primary RANOVAs in Results Sections 3.1 and 3.2 (below), using the Shapiro-Wilk test. Tests considered number of electrodes, DoF, electrode selection method and training condition. Eighty six percent of these tests affirmed normality ($p > 0.05$). In order to pursue one consistent set of statistical tests and because tests of normality have low statistical power when used on smaller sample sizes (Razali and Wah, 2011), the use of RANOVA was considered appropriate. When degree of sphericity (ϵ) was < 0.75 , degrees of freedom was adjusted by the method of Greenhouse-Geisser; and when $0.75 \leq \epsilon < 1$, it was adjusted by the method of Huynh-Feldt (Girden, 1992). *Post hoc* pair-wise comparisons were conducted using paired *t*-tests with Bonferroni correction for multiple comparisons. A significance level of $p = 0.05$ was used.

3. Results (see supplementary Table S1 for tabular summary of statistical results)

3.1. One-DoF models

Fig. 4 shows sample time-series EMG-force test results for the 1-DoF models (i.e., separate models formed for each DoF from trials that only examined each respective DoF). Fig. 5 shows summary RMS error results as a function of number of electrodes. For pre-determined electrode sites, a two-way RANOVA of RMS errors (factors: DoF; and

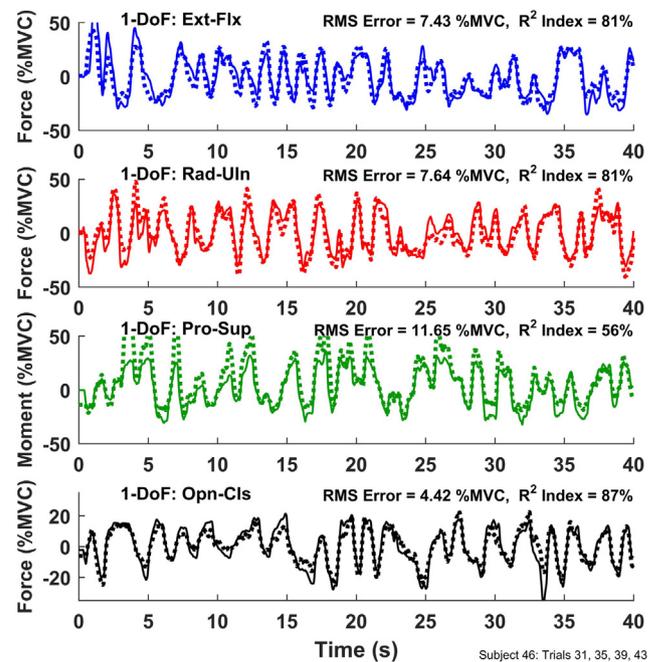


Fig. 4. Example time-series plots of 1-degree-of-freedom models, two backward selected electrodes. Solid lines are actual forces/moment, dashed lines are EMG-estimated. Note the difference in y-axis scales.

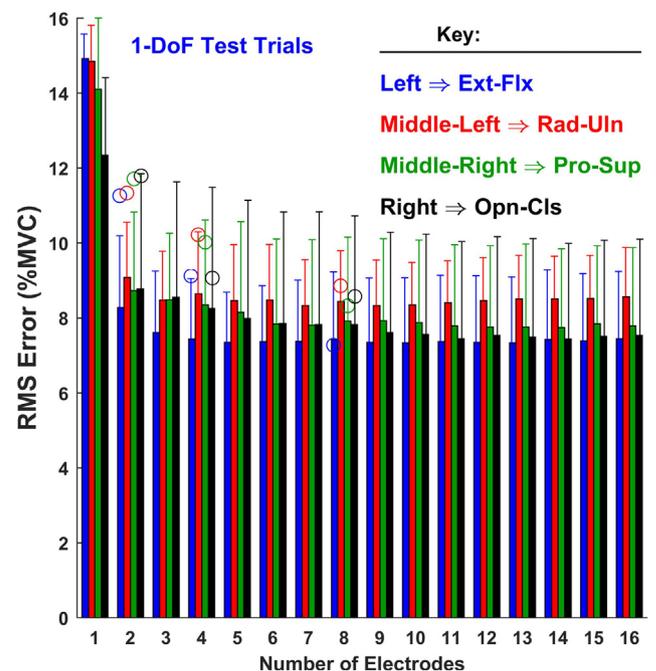


Fig. 5. Summary RMS error results: 1-degree-of-freedom models, nine subjects. For backward-selected electrode sites, bars show mean results and error lines show one standard deviation above the mean. For 2, 4 and 8 pre-determined electrode sites, “o” symbols show mean results.

number of electrodes, E) found that number of electrodes was significant [$F(3, 24) = 58, p = 10^{-11}$], but DoF was not [$F(3, 24) = 0.5, p = 0.70$]. *Post hoc* comparisons for number of electrodes found differences in all pairs ($p < 0.05$), with fewer electrodes always exhibiting higher error. For backward-selected electrode sites, a two-way RANOVA (factors: DoF; and number of electrodes, E) found that number of electrodes was significant [$F(1.8, 14.7) = 99, p_{GG} < 0.001$], but DoF was not [$F(3, 24) = 0.54, p = 0.66$]. *Post hoc* comparisons for

Table 1Mean \pm std. dev. RMS errors (%MVC), nine subjects, backward selected electrodes (left) and pre-determined electrodes (right).

Condition	DoF(s), backward selected electrodes				DoFs, pre-determined electrodes			
	Ext-Flx	Rad-Uln	Pro-Sup	Opn-Cls	Ext-Flx	Rad-Uln	Pro-Sup	Opn-Cls
1-DoF Models (2 electrodes)								
Assessed on 1-DoF trials	8.3 \pm 2.0	9.0 \pm 1.6	8.7 \pm 2.2	8.8 \pm 3.3	11.3 \pm 2.2	11.3 \pm 2.3	11.7 \pm 3.9	11.8 \pm 2.5
2-DoF Models (4 electrodes)								
Assessed on 1-DoF trials:								
Train with 1-DoF trials	7.3 \pm 1.4	8.0 \pm 1.2	7.9 \pm 1.0		8.3 \pm 0.9	8.7 \pm 1.2	8.9 \pm 1.1	
Train with 2-DoF trials	11.9 \pm 3.2	11.5 \pm 3.2	12.0 \pm 2.8		11.6 \pm 2.7	11.6 \pm 2.3	15.4 \pm 3.6	
Train with 1-, 2-DoF trials	7.4 \pm 0.8	8.0 \pm 1.0	7.9 \pm 1.0		8.5 \pm 0.8	8.8 \pm 0.9	9.2 \pm 1.0	
Assessed on 2-DoF trials:								
Train with 1-DoF trials	11.6 \pm 2.7	11.7 \pm 2.0	13.0 \pm 3.7		11.6 \pm 2.5	11.8 \pm 2.3	14.1 \pm 3.9	
Train with 2-DoF trials	9.0 \pm 3.0	8.6 \pm 2.3	7.8 \pm 1.2		9.5 \pm 2.1	9.5 \pm 1.9	10.2 \pm 1.9	
Train with 1-, 2-DoF trials	9.2 \pm 2.0	9.2 \pm 1.6	9.2 \pm 1.4		10.0 \pm 1.9	10.1 \pm 1.7	11.3 \pm 1.7	

number of electrodes only found that 1 backward-selected electrode exhibited higher error than more than 1 electrode ($p \leq 0.001$); and 10 electrodes exhibited lower error than 13 electrodes ($p = 0.006$; likely a statistical anomaly). Table 1 (top row) shows the RMS errors for two pre-determined electrode sites (right) and two backward-selected sites (left), the number of electrodes typically used for 1-DoF EMG-force.

Then, a three-way RANOVA (factors: DoF; number of electrodes E ; and electrode selection method) limited to 2, 4 and 8 electrodes was performed to directly compare the difference between pre-determined sites and backward selection. An interaction [$F(2, 16) = 25, p = 10^{-5}$] was found between the number of electrodes and the electrode selection method; the main effect of DoF was not significant [$F(3, 24) = 0.5, p = 0.70$]. Since prior research has already shown that fewer electrodes tend to generate higher errors, we next fixed the number of electrodes (2, 4 or 8) and pursued two-way RANOVAs (factors: DoF and electrode selection method). Backward selection had lower errors than pre-determined site selection for each of these three tests [$F(1, 8) \geq 7.5, p_{GG} \leq 0.03$].

3.2. Two-DoF models

Two-DoF models always estimated Opn-Cls combined with one wrist DoF (Ext-Flx, Rad-Uln or Pro-Sup) simultaneously. Fig. 6 shows sample time-series EMG-force test results during 2-DoF trials. Table 1 (lower rows) and Fig. 7 show a set of RMS error summary results.

Two-DoF Models Assessed on 1-DoF Trials: For pre-determined electrode sites: a three-way RANOVA (factors: DoF, number of electrodes and training condition) found significant main effects for number of electrodes [$F(1.1, 8.8) = 16, p_{GG} = 10^{-4}$] and training condition [$F(1.1, 9.0) = 152, p_{GG} = 10^{-10}$], but not DoF [$F(2, 16) = 3.8, p > 0.05$]. *Post hoc* analyses found that training with 2-DoF trials had higher errors than training with either 1-DoF trials or with both 1- and 2-DoF trials ($p < 10^{-5}$), and fewer electrodes always exhibited higher errors ($p < 0.02$).

For backward-selected electrode sites, the three-way RANOVA found interactions between training condition and each of the two other factors. Thus, separate two-way RANOVAs were pursued with training condition fixed. Results when training with 1-DoF trials were significant for the main effect of number of electrodes [$F(1.3, 10.6) = 37, p_{GG} = 10^{-4}$], but not for DoF [$F(2, 16) = 2.7, p = 0.1$]. *Post hoc* analysis of number of electrodes only found that 1 electrode exhibited higher error than more than 1 electrode ($p < 0.03$), 2 electrodes higher than 6–9 or 16 electrodes ($p < 0.04$), 3 electrodes higher than 6 and 9 electrodes ($p < 0.05$), 4 electrodes higher than 6, 7, 9 or 16 electrodes ($p < 0.05$), and 5 electrodes higher than 7 or 9 electrodes ($p < 0.03$). Differences in RMS error results when training with 2-DoF trials were

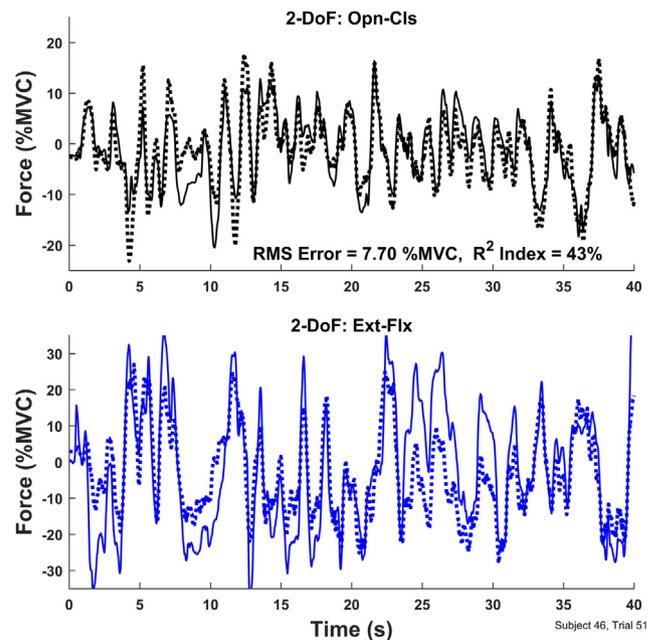


Fig. 6. Example time-series plots of 2-degree-of-freedom models applied to co-contraction trials (four electrodes). Key: solid lines = actual forces, dashed = estimated; black = Opn-Cls, blue = Ext-Flx. Four backward selected EMG channels and training from both 1- and 2-DoF trials. Note the difference in y-axis scales. (For interpretation of the references to colour in this figure legend, the reader is referred to the web version of this article.)

not significant for either the main effect of number of electrodes [$F(2.2, 17.9) = 0.5, p_{GG} = 0.6$] or DoF [$F(2, 16) = 0.5, p = 0.6$]. Results when training with both 1- and 2-DoF trials (Fig. 7, top) were significant for both main effects of number of electrodes [$F(1.5, 11.9) = 53, p_{GG} = 10^{-5}$] and DoF [$F(2, 16) = 6.7, p = 0.008$]. *Post hoc* analysis of number of electrodes only found that 1 electrode exhibited higher error than more than 2 electrodes ($p < 0.03$), 2 electrodes higher than more than 3 electrodes ($p < 0.03$), 3 electrodes higher than more than 5 electrodes ($p < 0.05$), and 4 electrodes higher than 12 or 13 electrodes ($p < 0.04$). *Post hoc* analysis of DoF only found that Opn-Cls & Ext-Flx had lower error than Opn-Cls & Rad-Uln ($p = 0.02$).

Table 1 (middle rows) shows the RMS errors for 4 backward-selected electrodes, the minimum number of electrodes expected for 2-DoF EMG-force. We computed a two-way RANOVA of RMS errors with number of electrodes fixed at four (factors: DoF, training condition). The main effect of DoF was not significant [$F(2, 16) = 0.2, p = 0.8$],

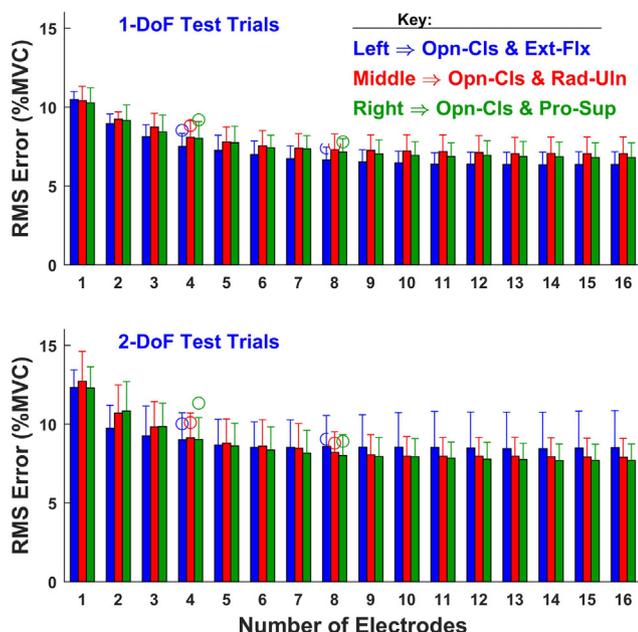


Fig. 7. Summary RMS error results: 2-degree-of-freedom (DoF) models, nine subjects. Top: testing on 1-DoF trials. Bottom: Models trained from both 1- and 2-DoF trials, tested on 2-DoF trials. For backward-selected electrode sites, bars show mean results and error lines show one standard deviation above the mean. For 4 and 8 pre-determined electrode sites, “o” symbols show mean results.

but training condition was significant [$F(1.1, 8.8) = 90, p = 0.8$]. *Post hoc* analysis found that training with only 2-DoF trials had higher errors than each of the other two training conditions ($p < 10^{-4}$).

Then, a three-way RANOVA (factors: DoF number of electrodes; and electrode selection method) limited to 4 and 8 electrodes was performed to directly compare the difference between pre-determined sites and backward selection. The main effects of number of electrodes [$F(1, 8) = 161, p_{GG} = 10^{-7}$] and electrode selection method [$F(1, 8) = 23, p_{GG} = 0.001$] were significant, but DoF was not [$F(2, 16) = 3.7, p > 0.05$]. *Post hoc* analyses found that eight electrodes had lower errors than four ($p = 10^{-7}$) and that backward selection had lower errors than pre-determined selection ($p = 10^{-3}$).

Two-DoF Models Assessed on 2-DoF Trials: For each of pre-determined and backward-selected electrode site methods, a three-way RANOVA of RMS errors (factors: DoF, number of electrodes and training condition) found interactions. As above, separate two-way RANOVAs were computed with each of the training conditions fixed. For each site selection method, training with only 1-DoF trials resulted in no significant differences for either number of electrodes [$F(2, 16) = 1.6, p = 0.23$ for pre-determined sites; $F(1.5, 12.0) = 0.7, p_{GG} = 0.5$ for backward-selected sites] or DoF [$F(2, 16) \leq 1.7, p \geq 0.22$].

For pre-determined electrode sites: when training with 2-DoF trials, number of electrodes and DoF interacted, thus three separate one-way RANOVAs were computed with each DoF pair fixed. Opn-Cls & Rad-Uln and Opn-Cls & Pro-Sup were significant ($p \leq 0.008$). *Post hoc* comparisons for each of these DoF pairs found that fewer electrodes always had higher error ($p < 0.03$). Results when training with both 1- and 2-DoF trials showed an interaction between number of electrodes and DoF. Thus, three separate one-way RANOVAs were computed with each DoF pair fixed. Each was significant ($p \leq 10^{-4}$). *Post hoc* comparisons for Opn-Cls & Rad-Uln and Opn-Cls & Pro-Sup each found that fewer electrodes always had higher error ($p < 0.004$).

For backward-selected electrode sites: results when training with 2-DoF trials were significant for the main effect of number of electrodes [$F(2.0, 15.8) = 66, p_{GG} = 10^{-6}$], but not for DoF [$F(2, 16) = 0.6, p = 0.5$]. *Post hoc* analysis of number of electrodes only found that 1 electrode exhibited higher error than more than 1 electrode ($p \leq 0.01$),

and 2 electrodes higher than more than 3 electrodes ($p \leq 0.02$). Results when training with both 1- and 2-DoF trials were significant for the main effect of number of electrodes [$F(1.6, 12.9) = 99, p_{GG} = 10^{-6}$], but not for DoF [$F(2, 16) = 0.07, p = 0.9$]. *Post hoc* analysis of number of electrodes only found that 1 electrode exhibited higher error than more than 1 ($p < 0.003$), 2 electrodes higher than more than 3 electrodes ($p < 0.003$), 3 electrodes higher than more than 5 electrodes ($p < 0.02$), 4 electrodes higher than more than 5 electrodes ($p < 0.03$), and 5 electrodes higher than 6 or 10–13 electrodes ($p < 0.05$).

Table 1 (lower rows) shows the RMS errors for 4 electrodes. We computed a two-way RANOVA of RMS errors with number of backward-selected electrodes fixed at four (factors: DoF, training condition). The main effect of DoF was not significant [$F(2, 16) = 0.03, p = 1.0$], but training condition was significant [$F(1.1, 8.8) = 23, p_{GG} = 0.001$]. *Post hoc* analysis found that training with only 1-DoF trials had higher errors than each of the other two training conditions ($p < 0.01$), and training with only 2-DoF trials had marginally lower error than training with 1- and 2-DoF trials ($p = 0.045$).

Then, a three-way RANOVA (factors: DoF; number of electrodes; and electrode selection method) limited to 4 and 8 electrodes was performed to directly compare the difference between pre-determined sites and backward selection. The main effects of number of electrodes [$F(1, 8) = 59, p_{GG} = 10^{-5}$] and electrode selection method [$F(1, 8) = 7.6, p_{GG} = 0.025$] were significant, but DoF was not [$F(2, 16) = 0.04, p = 0.96$]. *Post hoc* analyses found that eight electrodes had lower errors than four ($p = 10^{-5}$) and that backward selection had lower errors than pre-determined selection ($p = 0.025$).

3.3. Electrodes selected

For backward-selected electrodes, it is helpful to summarize the extent to which the selected electrode locations were distributed about the forearm. When selecting to two electrodes in 1-DoF models, there exist two interposing electrode distances. The average distance must equal 8 electrodes (out of 16 total). An interposing distance of 1 electrode denotes adjacent electrodes. Aggregating the results across four DoFs, two cross-validations and nine subjects, the mean \pm std. *minimum* interposing distance was $31 \pm 12\%$ of forearm circumference. When selecting to four electrodes in 2-DoF models, there exist four interposing distances (with an average distance of 4 electrodes). When training with both 1- and 2-DoF trials (same aggregation), the mean \pm std. of *each* interposing distance was $25 \pm 17\%$ of forearm circumference. Overall, the selected electrodes were rarely adjacent, but not necessarily spaced equally about the forearm (see [Supplementary Fig. S1](#) for distribution plots of these distances).

Another aspect of electrode site selection is found by comparing the similarity of selected sites between the two training folds of the cross validation. We did so for 2-DoF, four-channel models, trained using both 1- and 2-DoF trials. Considering all DoF pairs, on average 2.9 ± 0.60 sites were identically selected by both cross validation folds, 3.3 ± 0.50 selected sites were within one electrode distance of each other, and 3.9 ± 0.33 of the four selected sites were within two electrode distances of each other. Thus, there was substantial consistency between selected electrodes when comparing between training sets. (For Opn-Cls & Ext-Flx, [supplementary Fig. S2](#) depicts the order in which electrodes were removed as well as the four retained electrodes, for both folds of this model.)

4. Discussion

Offline EMG-force models have been used in a number of applied biomechanics-based applications for several decades, primarily in single joint studies or in multi-joint studies in which single electrodes are each located on a large muscle (e.g., gait and back studies). In contrast, studies of the hand-wrist are characterized by electrode

placement over the forearm wherein many smaller muscles lie adjacent to one another. Electrode site selection over smaller muscles is much harder to achieve (Cavanaugh et al., 1983; Clancy et al., 2017), and each surface EMG recording often receives contributions from multiple muscles. Further, EMG acquisition and analysis is typically only one component within an applied study, thus methods to simplify the recording apparatus via appropriate use of fewer electrodes are important.

We used linear regression modeling of the EMG-force relationship to investigate the role of number of conventional electrodes and their site selection on modeling performance. We found that a minimum of two backward selected electrodes are required for 1-DoF force estimation and a minimum of four for 2-DoF force estimation. The selected sites were somewhat dispersed about the circumference of the forearm (i.e., sufficient to record both agonist and antagonist muscle activity). Since EMG σ (the model input) is a unipolar quantity and hand/wrist force/moment (the model output) is bipolar with the DoFs independent, linear models should require at least two inputs per DoF, consistent with our findings. Additional backward selected electrodes showed essentially no improvement for 1-DoF models, and small progressive improvement for 2-DoF models.

In general, backward selected electrodes achieved better performance compared to the same number of pre-selected sites. For example, 4 backward selected sites performed about as well as 8 pre-selected sites when testing 2-DoF models on 2-DoF trials (Fig. 7). A challenge remains that 16 electrodes must still be initially applied in order to determine the backward-selected site locations. Thus, a protocol improvement (i.e., decreased EMG channels) is only achieved in situations in which a model can be “calibrated” at one time/place and then used subsequently—and only the subsequent use benefits from the decreased EMG channels. As an example of this benefit, an ergonomics study might calibrate EMG-force in a fixed EMG-force measurement apparatus, which is typically large and bulky, using a full complement of electrodes. Then the worker can transition to an applied task at another location and/or day (e.g., for assessment of hand-tool use directly at the workbench) only requiring the reduced number of electrodes. The worker’s hand-wrist forces can thus be estimated via EMG without being constrained by the calibration device and with simpler EMG apparatus (perhaps wireless). For field studies, optimal EMG-force performance would result, but with a much simpler and, thereby, more feasible set of electrodes. Of course, future research is required to demonstrate that such multi-day studies provide consistent day-to-day performance (c.f. Hwang et al., 2017; Waris et al., 2018). In addition, our pre-selected sites were spread equidistant around the forearm (a convenience available due to placement of our complete 16-electrode system), without respect for muscle anatomy. Pre-selected site location might lead to improved performance if the locations are anatomically assigned (Fougner et al., 2014).

We assessed 2-DoF models on both 1- and 2-DoF trials (since 2-DoF models would still be applied to 1-DoF tasks in many studies). We also trained 2-DoF models from 1-DoF trials, 2-DoF trials or both. Our overall results show that training with both 1- and 2-DoF trials is clearly advantageous. This result is undesired, since training would be simpler and quicker if only 1-DoF trials were required. However, this result is consistent with the principle that models formed via supervised learning are most representative of the data used to train them (Ljung, 1999; Smith et al., 2016); i.e., 2-DoF models might be expected to provide better test results when trained using similar 2-DoF tasks.

Note that we found higher average error when assessing 2-DoF models on 2-DoF trials compared to 1-DoF trials. However, direct comparison between these conditions is not appropriate. In 1-DoF assessment of 2-DoF models, errors in the second DoF were assessed, but their truth values were near zero (as the second DoF was not active). Hence, higher errors are expected in the 2-DoF trials, since their average %MVC level (across both DoFs) was much higher (Clancy et al., 2017). (Both DoFs were active, and higher effort levels produce higher

errors, in general.)

This study was an initial examination into number of EMG channels and their site selection for simultaneous estimation of *force-varying* hand grip (Opn-Cls) and one wrist DoF. Several limitations are evident. First, we used simple modeling (linear regression) and EMG processing, so as to focus our effort on the novel evaluation of electrode site selection for these hand-wrist tasks. More advanced models are known to reduce error (An et al., 1983; Clancy and Hogan, 1994, 1995, 1997; Dai et al., 2017; Gottlieb and Agarwal, 1971; Hasan and Enoka, 1985; Hashemi et al., 2015, 2012; Hogan and Mann, 1980a, b; Messier et al., 1971; Potvin and Brown, 2004; Sanger, 2007; Solomonow et al., 1986; Thelen et al., 1994), and can be added in future work. Second, we studied fixed-posture, dynamic contraction with a bandwidth of 0.75 Hz. Varying posture can alter the interpretation of EMG intent (Jiang et al., 2013). Third, our backward selection method for choosing electrodes (as a subset of the available 16) is not unique. Further, the two distinct folds (from cross-validation) did not necessarily select the same electrodes; although, we did observe consistency between the two folds. When choosing 4 electrodes from 16 total, there are 1820 combinations. Thus, a non-exhaustive search method seems advantageous. But, alternatives to backward selection exist, including selection based on anatomical locations (Fougner et al., 2014), forward stepwise selection and backward-forward stepwise combinations.

5. Conclusion

Offline EMG-force has seen limited study for multi-joint systems. For 2-DoF EMG-force estimation in the hand-wrist, we studied the roles of number of electrodes, method of electrode site selection, training condition, and degree of freedom pair. Two-DoF EMG-force was successfully accomplished with the use of four electrodes, with lower errors found when electrode sites are selected from 16 electrodes via backward stepwise selection. These models should be calibrated using both 1- and 2-DoF trials and error did not substantially vary as a function of which wrist DoF to pair with hand grip. With this condition, Table 1 (lower rows) shows that 2-DoF estimation had average RMS testing errors of 9.2 %MVC for each DoF pair.

Conflict of interest

Authors Martinez-Luna, Hunt, Farrell and Clancy are/have been employed by Liberating Technologies, Inc., which has a potential financial benefit from the results of this research.

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Appendix A. Supplementary material

Supplementary data to this article can be found online at <https://doi.org/10.1016/j.jelekin.2019.04.003>.

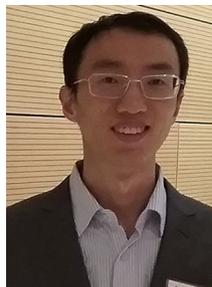
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