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Technical note

Prediction of forearm muscle activity during gripping

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Occupational exposure is typically assessed by measuring forces and body postures to infer muscular loading. Better understanding of workplace muscle activity levels would aid in indicating which muscles may be at risk for over-exertion and injury. However, electromyography collection in the workplace is often not practical. Therefore, a set of equations was developed and validated using data from two separate days to predict forearm muscle activity (involving six wrist and finger muscles) from grip force and posture of the wrist (flexed, neutral and extended) and forearm (pronated, neutral, supinated). The error in predicting activation levels of each forearm muscle across the range of grip forces, using the first day data (root mean square error; $RMSE_{model}$), ranged from 8.9% maximal voluntary electrical activation (MVE) (flexor carpi radialis) to 11% MVE (extensor digitorum communis). Grip force was the main contributor to predicting muscle activity levels, explaining over 70% of the variance in flexor activation levels and up to 60% in extensor activation levels, respectively. Inclusion of gender as a variable in the model improved estimates of flexor but not extensor activity. While posture itself explained minimal variance in activation without grip force (<10% MVE), wrist and forearm posture were required (with grip force) to explain over 70% of the variance of all six muscles. The validation process indicated good day-to-day reliability of each equation, with similar error for flexor muscle models but slightly higher error in the extensor models when predicting activity levels for the second day of data ($RMSE_{valid}$ ranging from 8.9% to 12.7% MVE). Detailed error analysis during validation revealed that inclusion of posture in the model effectively decreased error at grip forces above 25% maximum, but was detrimental at very low grip forces. This study presents a potential new tool to estimate forearm muscle loading in the workplace using grip force and posture, as a surrogate to use of a complex biomechanical model.

Keywords: Grip force; EMG; Posture; Regression; Prediction; Ergonomic tool

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1. Introduction

Epidemiological evidence has indicated a strong association between upper extremity musculoskeletal disorders, such as tendonitis and carpal tunnel syndrome, and jobs combining forceful grip exertions and deviated wrist postures (Armstrong *et al.* 1987). Consequently, a variety of observational, subjective and direct measurement methods have been developed to evaluate exposure to such risk factors (Wells *et al.* 1997, Li and Buckle 1999). However, these methods typically characterize external hand and finger forces without estimating muscular (internal) loads, thus limiting exposure assessment. More detailed information linking internal and external loads would improve understanding of how job task characteristics contribute to the risk of injury.

Electromyography (EMG) provides a physiological method of assessing muscle use and the magnitude of muscular loading and is directly related to muscular effort (Hägg *et al.* 2000). The correlation between EMG and force has enabled the development of mathematical relationships that predict grip force exertion using EMG (Armstrong *et al.* 1979, Duque *et al.* 1995, Claudon 1998, 2003), with recent efforts examining the effects of muscle selection (Hoozemans and van Dieën 2005, Keir and Mogk, 2005). While a physiologically based estimate of internal exposure is valuable for task analysis, EMG collection in the workplace is not always practical or feasible and is often limited to a single 'representative' muscle or a few select muscles. Regression modelling has been used successfully to estimate spinal loading (Fathallah *et al.* 1999) and more recently to predict shoulder muscle activity (Laursen *et al.* 2003). A similar approach may provide a practical tool to predict forearm muscle activity during gripping and may benefit ergonomists by suggesting muscles at risk during work tasks. The purpose of this study was to predict activity levels for six forearm muscles using grip force and posture, without the use of an elaborate biomechanical model.

2. Methods

The data used in this study were collected previously and described fully by Mogk and Keir (2003a); thus only an overview is provided here. Maximum grip force ($Grip_{max}$) was determined for ten healthy volunteers (five males and five females) in a mid-prone forearm and neutral wrist posture using a grip dynamometer (MIE Medical Research Ltd., Leeds, UK). Participants then performed exertions at five force levels (5, 50, 70 and 100% $Grip_{max}$ and 50 N) using the grip dynamometer (grip span of 5 cm) in each combination (nine in total) of three forearm postures (full pronation, neutral/mid-pronation and full supination) and three wrist postures (45° extension, neutral and 45° flexion). Participants were seated upright with their right forearm resting on an adjustable horizontal platform, with the wrist, hand and dynamometer not supported. Surface EMG was recorded from six forearm muscles: flexor carpi radialis (FCR), flexor carpi ulnaris (FCU), flexor digitorum superficialis (FDS), extensor carpi radialis, extensor carpi ulnaris (ECU), and extensor digitorum communis (EDC). EMG signals were normalized to the maximal voluntary electrical activation (MVE) after removal of signal bias (determined from a 'quiet' trial). Each trial lasted 10 s, during which the participant held the dynamometer while exerting minimal force ('baseline'), then ramped up to the target force level and held this for 3 s before returning to baseline. The grip dynamometer was zeroed (reset) at the baseline level with the participant holding it loosely (exerting approximately 10 N) in the desired posture; hence, baseline data corresponds to a force level 0% $Grip_{max}$. Calibration and experimental trials were performed on each of 2 d ('day 1' and 'day 2'), creating two datasets each comprising a total of 900 data points. Grip force and average muscle activation levels were normalized to $Grip_{max}$ and MVE values, respectively. It was decided a priori that 'day 1' data would be used to develop the equations and 'day 2' data would be used for validation.

2.1. *Model (equation) development*

Equations were developed to predict average EMG (AEMG) for each of the six forearm muscles from grip force and posture data (day 1) using forward stepwise regression analyses (STATISTICA v6.0; StatSoft Inc., Tulsa, OK, USA). AEMG was the dependent variable (in %MVE) and was predicted by combinations of grip force and posture. Subsets of independent variables were systematically selected and included in each model if their coefficients were significant at a level of $p < 0.05$. Analyses included linear, factorial and polynomial regressions to determine which mathematical arrangement was the best fit to the data and minimized prediction error. All models included the AEMG and measured grip force data from each of the five force exertions (5, 50, 70 and 100% $Grip_{max}$, plus the 50 N trial (with the 50 N converted into a relative force level)), in each combination of wrist and forearm posture (450 data points). Equations were developed both with and without baseline data (0% $Grip_{max}$). The muscle activity prior to each exertion was used to calculate a mean posture-specific baseline activation level, since baseline activity did not vary with the target force to be exerted (Mogk and Keir 2003a). This effectively reduced baseline data from 450 to 90 data points, resulting in a 540 point dataset for equations developed using baseline data and a 450 point dataset for equations without baseline data.

Equations to predict the AEMG activity of each forearm muscle were developed using posture alone, grip force alone and grip force with each combination of posture variables. Forearm posture was input nominally using dummy variables. Wrist posture was input into each model in two formats, separately: 1) as nominal data using dummy variables; or 2) as measured wrist angle (°). Equations were developed both with and without gender as a variable.

The accuracy with which each model predicted muscle activity was judged on goodness of fit (adjusted r^2_{model}) and overall error magnitude. Root mean square error ($RMSE_{model}$) and mean absolute difference (MAD_{model}) were calculated over the full range of grip forces for each model (expressed as %MVE). The error measures represent the residual difference between observed and predicted AEMG values.

2.2. *Model (equation) validation*

All models were validated by inputting day 2 data into the day 1 equations. As with equation development, explained variance (r^2_{valid}), $RMSE_{valid}$ and MAD_{valid} between observed and predicted values were used to evaluate how well day 2 AEMG was predicted over the full range of grip forces. Additionally, six specific ranges of grip force were examined (0%, 5%, 50 N, 25–50%, forces $\leq$50% and forces $>$50% $Grip_{max}$) to determine whether muscle activations were predicted equally well throughout the full range of forces. The 50 N trials were examined separately since they represented a relative target force that varied with individual grip strength from 8.8% to 24.2% $Grip_{max}$. The 25–50% $Grip_{max}$ range incorporated all exertions effectively greater than 50 N but less than or equal to 50%.

3. Results

3.1. *Equations (model development)*

The inclusion of baseline data (0% $Grip_{max}$) in models developed using grip force and posture (wrist and forearm) resulted in overall $RMSE_{model}$ values below 10.5% MVE for all muscles. However, detailed error analysis revealed a large number of negative muscle activity predictions at 'zero' grip force, thus prompting the decision to present only equations developed without baseline data. The general mathematical form for predicting the activity of each muscle is found in equation 1. Although second order models provided only minimal improvement over factorial and simple linear regression for the flexor muscle models, the r^2_{model} and $RMSE_{model}$ for the extensor muscles were improved by as much as 6.5% and 1.0%, respectively.

$$AEMG_i = (a_1 \cdot GF) + (b_1 \cdot GF^2) + (a_2 \cdot W_{Ex}) + (a_3 \cdot W_{Fl}) + (a_4 \cdot FA_{Pr}) + (a_5 \cdot FA_{Su}) + (a_6 \cdot G) + c \quad (1)$$

where $AEMG_i$ is average muscle activation (in %MVE) for each muscle (i ranging from 1 to 6); GF is grip force (in %$Grip_{max}$); W_{Ex} is wrist extension and W_{Fl} is wrist flexion with a value of 1 (otherwise, 0 indicates neutral wrist posture); FA_{Pr} is pronation and FA_{Su} is supination of the forearm with a value of 1 (otherwise, 0 indicates neutral/mid-pronation); G is gender (with male = 0 and female = 1); a_i and b_i represent first and second order coefficients, respectively; c is a constant.

A list of the coefficients and error terms for each equation is found in table 1. The GF^2 coefficient became non-significant in flexor muscle models once wrist and forearm posture (or wrist posture alone) were included with grip force (table 1). This was only observed when gender was added to flexor muscle equations. Although coefficients were included if significant at $p < 0.05$, most were significant at $p < 0.001$.

3.2. *Contributions of model components*

Gender alone did not explain any of the variance (0%) in muscle activation levels. However, when included with grip force, gender improved the r^2_{model} and $RMSE_{model}$ for the flexor muscle models by as much as 3.8% and 0.8%, respectively, but added nothing to extensor muscle models. Posture (wrist and/or forearm posture) alone did not predict muscle activity well, explaining only 0–9% of the muscle activity variance. As seen in table 1, grip force alone explained over 70% of the variance for all flexor muscle models, but less than 60% for the extensor muscle models, with $RMSE_{model}$ values ranging from 9.7% for FCR (MAD_{model} = 7.4%) to 13.4% for EDC (MAD_{model} = 9.8%). Compared to grip force alone, adding wrist posture improved r^2_{model} and $RMSE_{model}$ by as much as 12.5% and 2.1%, respectively. Use of the measured wrist angle (°) resulted in slightly weaker models than the nominal form (using dummy categorical variables), thus the nominal form was used. Forearm posture had little effect on predicting the activity of each muscle, with the exception of ECU, which improved r^2_{model} by 10.3% and $RMSE_{model}$ by 1.8%. When combined with grip force, the inclusion of both wrist and forearm posture improved the r^2_{model} of all models to at least 70% and reduced $RMSE_{model}$ by 0.7–2.6% MVE (table 1). All muscles were predicted within 11% MVE ($RMSE_{model}$) over the full range of grip forces.

Table 1. Coefficients for quadratic models using grip force (GF) only and GF with wrist and forearm posture (GF + P) as input. Gender was also included, but was only significant for flexor muscle equations. Explained variance (r^2_{model}) and the overall root mean square error for each model ($RMSE_{model}$) and validation ($RMSE_{valid}$) are shown to indicate how well muscle activity was predicted across the full range of grip force levels.

		Equation coefficients								Goodness of fit and error			
Muscle (m_i)	Input variables	a_1 (GF)	b_1 (GF^2)	a_2 (W_{Ex})	a_3 (W_{Fl})	a_4 (FA_{Pr})	a_5 (FA_{Su})	a_6 (G)	c	r^2_{model}	$RMSE_{model}$	r^2_{valid}	$RMSE_{valid}$
FCR	GF	0.6900	−0.0016					−4.0415	0.1778	0.741	9.7	0.749	9.3
	GF + P	0.5591	*	−3.7967	4.6095	−2.9588	2.2677	−4.0624	1.4283	0.780	8.9	0.771	8.9
FCU	GF	0.7082	−0.0015					−8.0652	1.7812	0.708	11.1	0.712	10.4
	GF + P	0.5885	*	*	6.6396	3.6069	−2.9013	−8.1042	−3.4076	0.743	10.4	0.720	10.3
FDS	GF	0.7581	−0.0022					−5.3991	0.8578	0.712	10.7	0.702	10.5
	GF + P	0.5830	*	−4.9691	7.1060	−3.3869	*	−5.4393	2.8834	0.768	9.6	0.745	9.8
ECR	GF	0.9175	−0.0047					*	2.6622	0.601	12.2	0.606	12.4
	GF + P	0.8203	−0.0033	*	12.0914	*	−5.8954	*	0.8289	0.701	10.5	0.704	10.8
ECU	GF	0.8469	−0.0036					*	2.2093	0.586	13.1	0.521	13.8
	GF + P	0.7606	−0.0023	−4.1563	6.6250	10.0968	−5.9740	*	0.1799	0.733	10.5	0.619	12.7
EDC	GF	1.0174	−0.0058					*	1.7290	0.563	13.4	0.540	13.0
	GF + P	0.8836	−0.0038	−7.4372	10.9001	*	−4.8737	*	2.6713	0.702	11.0	0.649	11.5

GF = normalized grip force (%$Grip_{max}$); W = nominal wrist posture (W_{Ex} = 1 and W_{Fl} = 0 for extension, both = 0 for neutral, W_{Ex} = 0 and W_{Fl} = 1 for flexion); FA = nominal forearm posture (FA_{Pr} = 1 and FA_{Su} = 0 for pronation, both = 0 for neutral, FA_{Pr} = 0 and FA_{Su} = 1 for supination); G = gender (male = 0, female = 1); FCR = flexor carpi radialis; FCU = flexor carpi ulnaris; FDS = flexor digitorum superficialis; ECR = extensor carpi radialis; ECU = extensor carpi ulnaris; EDC = extensor digitorum communis.
*Coefficients with $p > 0.05$ were not included in each equation.

3.3. *Model validation*

Day 2 flexor muscle activity was predicted marginally better than day 1 activity, while day 2 extensor activity was predicted marginally less well than day 1 (table 1). Evaluation of the models over specific ranges of grip force found that the error increased as grip force increased (as seen moving from left to right in table 2, which shows the validation errors when evaluated within the various grip force ranges). Limiting validation input to forces less than or equal to 50% $Grip_{max}$ revealed RMSE to be reduced by as much as 2.6% from the overall full-range $RMSE_{valid}$ for the same muscle. Further partitioning of input forces below 50% revealed that only those forces exerted during the 5% $Grip_{max}$ and 50 N trials had errors lower than overall $RMSE_{valid}$. The RMSE of predicted AEMG for grip forces greater than 50 N but lower than 50% (effectively 25–50% $Grip_{max}$) was up to 5.1% higher than the full-range $RMSE_{valid}$ for predicted AEMG grip force alone and up to 3.5% higher for the model including posture (grip force + posture) (table 2). For grip forces greater than 50%, error in predicting AEMG was up to 4.0% MVE larger than for the prediction over the entire range of forces. Including gender in the flexor muscle models (FCR, FCU and FDS) tended to improve muscle activity estimates for forces greater than 50% $Grip_{max}$, but increased error slightly for 5% grip exertions.

4. Discussion

The equations developed in this study predicted the activity of six forearm muscles to within 11% (MVE) error and 70% explained variance using grip force with wrist and forearm posture. Inclusion of gender as a predictor variable improved estimates of flexor but not extensor muscle activity, resulting in linear models for flexor muscles once wrist posture was added. While grip force alone produced r^2_{model} values greater than 70% for flexor muscles and up to 60% for extensor muscles, posture data alone was a poor predictor of muscle activity ($r^2 < 10\%$). When input along with grip force, wrist posture improved r^2_{model} as much as 14% and decreased the overall $RMSE_{model}$ by 2% MVE. Validation analysis of specific grip force ranges indicated that the greatest accuracy in predicting muscle activations was at lower grip forces (below 50% $Grip_{max}$). Overall, these findings suggest that regression modelling can be used to estimate subject-independent forearm muscle loading patterns during isometric gripping tasks.

As expected, regression equations developed using the full complement of inputs generated the most accurate estimates of activity for each muscle. Interestingly, gender improved flexor muscle equations, despite non-statistical differences in either relative grip force or corresponding muscle activation between males and females (Mogk and Keir 2003a). As seen in the overall error estimates (r^2_{model} and $RMSE_{model}$) shown in table 1, the activity of each flexor muscle was more strongly related to grip force than the activity of the extensors, as shown previously (Keir and Mogk 2005). As reflected by the sign of individual equation coefficients, muscle activations decreased with wrist extension and increased with flexion, relative to neutral wrist posture. Interestingly, nominal wrist posture resulted in lower error for estimated muscle activity than measured wrist angles. While this may reflect low wrist angle variability in the study, this simplification indicates the potential utility of a posture matching approach in place of measurement with wrist goniometers. Inclusion of forearm posture made little improvement in the model over grip force alone, but enabled the prediction of gravity-based increases in flexor and extensor activity associated with maintaining supinated and pronated postures, respectively.

Inclusion of all available data was not always beneficial. Although inclusion of baseline (0% $Grip_{max}$) data reduced the overall $RMSE_{model}$ for each muscle to below 10.5% MVE, this was only true for grip forces below 5% $Grip_{max}$, with an increase in error for all other force levels. Previous studies have suggested that incorporating baseline data improved estimates of muscle force (Buchanan *et al.* 1993) and grip force (Keir and Mogk 2005). In the current study, inclusion of the baseline AEMG during model development led to two issues. First, equations predicted negative activity for all six muscles if grip force was set to zero and the wrist was in extension, which is not physiologically possible. Second, baseline activity was always predicted to increase from extension to flexion for all six muscles, which is contrary to the observed extensor activation patterns in pronation (Mogk and Keir 2003a). These factors led to the exclusion of baseline data from all models and greatly reduced predictions of negative muscle activity.

The validation process used could be described as an examination of day-to-day reliability, with additional inspection of specific ranges of grip force. In general, muscle activity for day 2 data was predicted with similar or better accuracy than the day 1 data, from which the equations were developed (table 1). While the error for forces below 50% $Grip_{max}$ was lower than the whole range $RMSE_{valid}$, further analysis revealed this to be true only for forces less than 50 N (below 25% $Grip_{max}$ for all participants) (table 2). The error associated with muscle activity predictions for grip forces between 25–50% $Grip_{max}$ was slightly larger (1–5%) than overall $RMSE_{valid}$, and was at least partially due to increased error in trials with the wrist flexed. The increased error found in flexed postures is likely explained by a previous finding by the authors of equal or greater magnitude of EMG in spite of decreased grip force (Mogk and Keir 2003a). The benefits of including posture as an input variable were most evident with grip forces above 25% $Grip_{max}$, while inclusion of posture was actually detrimental for activity related to forces of 5% $Grip_{max}$ and below (table 2). The differences in error noted between postures were likely influenced by biases introduced by the need to overcome passive muscle forces (Keir *et al.* 1996) and antagonist co-contraction, and the need to work against gravity (e.g. for extensor muscles in pronation). This was most evident during low-level force exertions, during which such biases would have had their largest relative effects.

Two other additional tests were performed to investigate the robustness of muscle activity predictions. Similar to Lee *et al.* (2003), who input predicted activity levels in an EMG-driven model, the authors first substituted predicted muscle activity levels from the current study into established grip force equations (Keir and Mogk 2005). Predicted grip force values based on estimated muscle activations from the current study were consistently closer to measured grip force values than when recorded EMG data was used, regardless of equation complexity. This process, although somewhat self-fulfilling, does provide internal validity to both models. The second test utilized a modified version of the ‘exertion’ rating scale used in the Strain Index (Moore and Garg 1995). Each measured grip force level was assigned to one of five bins representing 20% increments from 0 to 100% $Grip_{max}$. Equations were then developed to predict muscle activity levels from these graded force levels, using the same methods described in the current study. Greater accuracy was found using the 5-point scale than the measured grip force. This suggests that perceived exertion scales may be used if direct force measurements are unavailable, as it has previously been shown that grip exertions can be perceived to within 3% of their measured value (Marshall *et al.* 2004). This method could provide a simple addendum to observational methods such as the Strain Index (Moore and Garg 1995) or RULA (McAtamney and Corlett 1993).

Table 2. Validation error (root mean square error (RMSE) and mean absolute difference (MAD) measured in % maximal voluntary electrical activation (MVE)) associated with testing each quadratic muscle equation using specific ranges of grip force (GF) from day 2 data. Two models are presented for each force range: (i) for GF only; (ii) including GF with wrist and forearm posture (GF + P). All flexor muscle models also include gender.

Muscle	Error	5%		50 N*		$\leq$50% $Grip_{max}$†		25–50% $Grip_{max}$‡		>50% $Grip_{max}$		Full range§	
(m_i)	measure	GF	GF + P	GF	GF + P	GF	GF + P	GF	GF + P	GF	GF + P	GF	GF + P
FCR	RMSE	2.5	4.3	4.3	4.7	8.0	7.6	11.9	10.7	11.5	11.1	9.3	8.9
	MAD	2.2	3.5	3.6	3.7	5.5	5.7	9.4	8.7	9.3	9.0	6.8	6.8
FCU	RMSE	4.3	5.9	5.3	6.3	9.5	9.2	13.7	12.6	12.1	12.2	10.4	10.3
	MAD	4.1	4.9	4.4	5.1	7.0	7.1	11.3	10.2	9.9	10.0	8.0	8.1
FDS	RMSE	3.8	5.6	6.2	6.3	10.1	9.2	14.7	12.5	11.3	10.8	10.5	9.8
	MAD	3.2	4.6	4.8	4.8	7.2	6.9	11.9	10.2	9.3	8.8	7.9	7.5
ECR	RMSE	3.9	6.5	7.2	6.7	11.2	9.6	16.3	12.7	14.6	12.9	12.4	10.8
	MAD	3.0	5.4	5.7	5.1	7.8	7.3	13.0	10.3	12.3	10.4	9.3	8.3
ECU	RMSE	3.8	7.1	8.2	8.0	11.2	10.1	15.9	13.0	17.8	16.7	13.8	12.7
	MAD	3.2	5.6	7.2	6.1	8.5	7.7	13.3	10.5	15.4	14.0	10.8	9.8
EDC	RMSE	5.6	8.3	7.2	7.5	12.5	11.3	18.1	15.0	14.1	11.8	13.0	11.5
	MAD	3.8	6.8	6.2	5.8	8.8	8.5	14.5	11.8	11.4	9.6	9.6	8.9
Number of data points		90		90		300		120		150		450	

*The relative effort level of the 50 N trials was dependent on each participant's strength and ranged from 8.8%–24.2% $Grip_{max}$.

†Includes 5% $Grip_{max}$ trials, 50 N trials and any other trials where GF was $\leq$50% $Grip_{max}$.

‡Includes all trials where greater than 50 N but less than 50% $Grip_{max}$ was achieved, including trials in which the target force was greater than 50%, but the actual force exerted was limited by posture.

§The Full range column corresponds to the $RMSE_{valid}$ in table 1.

$Grip_{max}$ = maximum grip force; FCR = flexor carpi radialis; FCU = flexor carpi ulnaris; FDS = flexor digitorum superficialis; ECR = extensor carpi radialis; ECU = extensor carpi ulnaris; EDC = extensor digitorum communis.

There are some limitations to the current study. Muscle activity predictions may differ in more complex conditions. A recent study by Hoozemans and van Dieën (2005) indicated that using a dynamic calibration process may further improve estimations, but that use of a set grip span for all subjects would have a minimal effect when predicting grip force from forearm EMG. In addition it should be noted that EMG crosstalk was unlikely in the present experimental arrangement, as indicated by a previous study examining electrode placements and spacing (Mogk and Keir 2003b).

While the current study has laid the groundwork for developing a practical method to estimate muscle loading, other aspects must be incorporated to reflect the complexity of hand intensive tasks, including dynamic exertions and different grip types, as well as tasks requiring additional effort for stabilization during push/pull exertions or to counter a tool applied torque. When combined with repetition and duration information, this approach may be useful in determining cumulative loading of the hand and wrist. This study represents an initial effort that has created a viable ergonomic tool to assess the potential for muscle overload using grip force and posture, as an alternative to using a complex biomechanical model.

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