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Evaluation of Three Methods for Determining EMG-Muscle Force Parameter Estimates for the Shoulder Muscles

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Abstract

Background—Accurate prediction of *in vivo* muscle forces is essential for relevant analyses of musculoskeletal biomechanics. The purpose of this study was to evaluate three methods for predicting muscle forces of the shoulder by comparing calculated muscle parameters, which relate electromyographic activity to muscle forces.

Methods—Thirteen subjects performed sub-maximal, isometric contractions consisting of six actions about the shoulder and two actions about the elbow. Electromyography from 12 shoulder muscles and internal shoulder moments were used to determine muscle parameters using traditional multiple linear regression, principal-components regression, and a sequential muscle parameter determination process using principal-components regression. Muscle parameters were evaluated based on their sign (positive or negative), standard deviations, and error between the measured and predicted internal shoulder moments.

Findings—It was found that no method was superior with respect to all evaluation criteria. The sequential principal-components regression method most frequently produced muscle parameters that could be used to estimate muscle forces, multiple regression best predicted the measured internal shoulder moments, and the results of principal-components regression fell between those of sequential principal-components regression and multiple regression.

Interpretation—The selection of a muscle parameter estimation method should be based on the importance of the evaluation criteria. Sequential principal-components regression should be used if a greater number of physiologically accurate muscle forces are desired, while multiple regression should be used for a more accurate prediction of measured internal shoulder moments. However, all methods produced muscle parameters which can be used to predict *in vivo* muscle forces of the shoulder.

Keywords

principal-components regression; shoulder; EMG; muscle force model

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Introduction

Individual muscle forces across a joint can be estimated using optimization-based or electromyography (EMG) -driven models. Many EMG-driven muscle force prediction models rely on using maximal contractions to normalize EMG measurements. Accurate estimations of maximal EMG values are not always obtained when elicited from maximal voluntary contractions, and, if not attained, can result in the prediction of inaccurate muscle forces and joint moments (Buchanan et al., 2004). An alternative to using maximal EMGs for normalization is to use multiple regression (An et al., 1983) to determine muscle parameters, which related EMG measurements to muscle forces. However, EMG multi-collinearity is present when recording from multiple muscles about a given joint (Hughes and Chaffin, 1997; Kutch and Buchanan, 2001; Meek et al., 1990), which has two potentially deleterious outcomes when estimating muscle forces. First, there can be substantial variability in muscle forces between trials (Hughes and Chaffin, 1997) and second, muscle forces are likely over-estimated because multi-collinearity represents information redundancy. Many models assume that EMG activity is associated with the production of muscle forces for the primary purpose of producing joint moments and disregard the notion that muscle forces assist in providing joint stability.

Principal-components regression can also be used to determine muscle parameters, does not rely on maximal EMG measurements, and resolves EMG multi-collinearity (Hughes and Chaffin, 1997; Meek et al., 1990). This technique has been successfully utilized to predict elbow flexion torque using sub-maximal contractions (Kutch and Buchanan, 2001).

The purpose of this study was to evaluate three methods for determining muscle force parameters, using data from a sub-maximal muscle contraction protocol and does not require normalization of EMG measurement data. The three methods of muscle parameter estimation included traditional multiple linear regression applied to three-axis moments, principal-components regression applied to three-axis moments, and sequentially-determined muscle parameters using principal-components regression applied to single-axis moments.

Methods

Thirteen healthy volunteers (8 male, 5 female; mean age 23.4 y/o (SD 3.8), range 18–31 y/o; mean body mass index 23.8 (SD 4.2)) participated in the current study; informed consent was obtained from all study participants, and the protocol was approved by the University Institutional Review Board. All subjects were screened for health history and were admitted only if they were without history of back, shoulder, arm, wrist, and hand pathology.

Subject preparation

Anthropometric measurements were obtained which included weight, upper arm length, forearm length, and hand length for the right arm; the right arm was used for the entire protocol and all subjects were right-hand dominant. A sub-maximal protocol was used during the muscle parameter calibration procedure, however isometric, maximum voluntary contractions (MVCs) were initially obtained to determine appropriate sub-maximal cutoffs for each subject. A sub-maximal cutoff of 50% MVC was chosen with the intent to invoke significant muscle activity. Subjects were seated and restrained in a Biodex System 3 dynamometer (Biodex Medical Systems Inc., Shirley, NY, USA) with the right arm positioned in the calibration posture consisting of 30° shoulder abduction and 90° elbow flexion with neutral humeral and forearm rotation. Separate MVCs were performed for six actions about the shoulder (abduction, adduction, internal rotation, external rotation, flexion, and extension) and two actions about the elbow (flexion and extension). Subjects performed between 3 and 6 MVCs (3 second duration) for each of the 8 actions; MVCs were performed until the last MVC measurement

was lower than the previous MVC measurement for each action; 1 minute rest periods were given between each MVC. The highest value for each action was used to determine the 50% strength cutoff for the respective action.

Surface EMG electrodes and intramuscular wire electrodes were placed around and inserted into the shoulder, respectively. Only muscles which act across the glenohumeral joint were included in the current study. Surface electrodes consisted of pairs of bipolar silver-silver chloride surface electrodes (2.2 cm diameter; Ambu Inc., Glen Burnie, MD, USA) and were placed on the long and short heads of the biceps, the long head of the triceps, the sternocostal and clavicular portions of the pectoralis major, the anterior, middle, and posterior portions of the deltoid, the infraspinatus, and the latissimus dorsi. Each electrode pair was spaced 2.2 cm between centers and was placed according to previously-defined locations (Basmajian and Blumenstein, 1985; Cram et al., 1998; Paton and Brown, 1995; Sakurai et al., 1998; Scheving and Pauly, 1959). Electrode pair resistance and potential difference were measured and if either measurement was vastly greater than that of the other electrode pairs (approximately two times by visual inspection), this electrode pair was removed, the skin was cleaned, and new electrodes were placed in the same locations. Intramuscular wire electrodes (VIASYS Healthcare, Madison, WI, USA) were used in the subscapularis, supraspinatus, and teres major, and were inserted by an experienced orthopaedic surgeon (JEC). Prior to insertion, the skin was carefully prepared and sterilized. A postero-medial approach (Kadaba et al., 1992) was used for the insertion of the subscapularis electrode (100 mm x 23 awg cannula), the teres major electrode (30 mm x 25 awg cannula) was inserted with a direct posterior approach (Delagi et al., 1975), and the supraspinatus electrode (30 mm x 25 awg cannula) was inserted using a superior approach (Kelly et al., 1996). Intramuscular electrode placement was verified by functional muscle testing (Cram et al., 1998; Paton and Brown, 1995; Sakurai et al., 1998). The location of the teres major wire electrode was in question for many of the subjects for two reasons. First, the target muscle is small and it is difficult to be certain of the intramuscular electrode placement, and second, the teres major was seen to be active during both agonist and antagonist actions during the functional muscle testing. Considering these issues, the EMG data from the teres major was not used to compute muscle parameters.

The subject's arm was positioned with 90° of elbow flexion (consistent with the calibration posture) to conform to a 90° aluminum mounting plate. The arm, with the aluminum plate, was casted from the midshaft of the humerus to the wrist in order to minimize internal shoulder moments at the shoulder induced by elbow flexion and extension. The mounting plate also provided a means to rigidly affix the subject's arm to the testing apparatus.

Calibration trials

Subjects were seated and restrained in a Biodex System 2 dynamometer (Biodex Medical Systems Inc., Shirley, NY, USA) and positioned in the calibration posture. Experimental data were not collected using the Biodex torque cell and computer but were measured using a six degree-of-freedom load cell (JR3 Inc., Woodland, CA, USA) affixed to the Biodex dynamometer support. A fabricated aluminum fixture, with a handle that was adjustable to forearm length, was attached to the top of the load cell, to which the casted 90° aluminum mounting plate was secured (Figure 1). Calibration trials consisted of isometric, sub-maximal, ramp contractions, and were performed for the same 8 actions as the MVCs. Three trials of each ramp contraction were performed, resulting in a total of 24 ramp contractions per subject. Each of the 24 ramp contractions were performed one at a time in a randomized order and were separated by 1 minute breaks to prevent fatigue. For each ramp contraction, subjects were instructed to steadily increase (2 second duration) the contraction intensity from 0 to 50% of their sub-maximal cutoff for the respective action, and then steadily decrease (2 second duration) the contraction intensity. Ramp contractions consisting of elbow flexion and

extension were included to account for the contribution of the long and short heads of the biceps and the long head of the triceps as these are biarticular muscles of the shoulder and the elbow; these were performed with the arm uncasted. A custom-written graphical interface (LabVIEW, National Instruments Corporation, Austin, TX, USA) was used to give the subject visual feedback which displayed the subject's 50% sub-maximal cutoff for each action and provided a set pace at which to perform the ramp contractions.

Data processing

Data from the calibration trials were collected on a personal computer using MotionMonitor Software (Innovative Sports Training Inc., Chicago, IL, USA). All EMG signals were recorded at 1000 Hz with a Noraxon Myosystem 2000 EMG system (Noraxon Inc., Scottsdale, AZ, USA) and were filtered using a 4th order Butterworth filter (4 Hz low-pass cutoff; Winter, 1990; Buchanan et al., 2004) and subsequently post-processed using methods presented by Lloyd and Besier (2003), which synchronize muscle activation and muscle force production by accounting for electromechanical delay. Load cell data were recorded at 1000 Hz and processed using a custom-written Matlab script (The Mathworks Inc., Natick, MA, USA) with a 2nd order Butterworth filter (8 Hz low-pass cutoff). Internal shoulder moments were computed using the subject anthropometry and the moment and force data from the load cell. The 24 ramp contraction trials were placed into 3 groups according to first, second, and third time they were performed according to the protocol. This grouping was termed a set of trials, where each set of trials consisted of internal moment and EMG data arrays of one of each of the 8 actions of the ramp contractions.

Muscle parameter calculations

Three different methods were used to estimate muscle parameters relating EMG to muscle forces: traditional multiple linear regression (MR), principal-components regression (PCR), and a sequential method using principal-components regression (PCR-S). For each of the three sets of trials, a separate set of muscle parameters was determined by each muscle parameter estimation method, thus 3 sets of muscle parameters were computed for each method. Furthermore, it should be noted that a single muscle parameter was calculated for each muscle for each set of trials, and muscle parameters can be used to predict muscle forces from EMG measurements obtained during any action of the shoulder.

The current study defined the relationship between observed responses $\mathbf{y}$ and predictor variables $\mathbf{X}$, expressed in matrix notation, as:

$$\mathbf{y} = \mathbf{X}\boldsymbol{\beta} + \boldsymbol{\varepsilon} \quad (1)$$

where $\mathbf{y}$ is an $n \times 1$ vector of internal shoulder moments (n measurement time points), $\mathbf{X}$ is an $n \times m$ matrix of muscle moment arm-weighted EMG measurements (m muscles where $m = 1, 2, \dots, 12$), $\boldsymbol{\beta}$ is an $m \times 1$ vector of muscle parameters (regression coefficients), and $\boldsymbol{\varepsilon}$ is an $n \times 1$ random error vector.

Multiple linear regression techniques have been used to determine muscle parameters for the shoulder (Laursen et al, 1998), the ankle and knee (Olney and Winter, 1985), and the low back (Hughes and Chaffin, 1997). For the method of multiple linear regression, least squares predicted muscle parameters $\hat{\boldsymbol{\beta}}$ were determined in the traditional fashion (similar to that of Hughes and Chaffin, 1997) by:

$$\hat{\boldsymbol{\beta}} = (\mathbf{X}'\mathbf{X})^{-1}\mathbf{X}'\mathbf{y} \quad (2)$$

For the methods of PCR and PCR-S, principle components were used to reduce the dimensionality of the parameter space used for least squares fitting; see Draper and Smith

(1981) and Montgomery and Peck (1992) for additional information on PCR. The correlation between the predictor variables is defined by $\mathbf{R}$, an $m \times m$ correlation matrix, which can be decomposed:

$$\mathbf{R} = \mathbf{T}\mathbf{\Lambda}\mathbf{T}' \quad (3)$$

where $\mathbf{\Lambda}$ is an $m \times m$ diagonal matrix of eigenvalues ($\lambda_1, \lambda_2, \dots, \lambda_m$), and $\mathbf{T}$ is an $m \times m$ orthogonal matrix whose columns are the eigenvectors of $\mathbf{R}$ (i.e., principal components) and correspond to the associated eigenvalues. The magnitude of the individual eigenvalues, relative to the sum of all the eigenvalues, is an indicator of the amount of variance in the data attributed to each eigenvector. To reduce the dimensionality of the original dataset $\mathbf{X}$, the principal components are arranged in the order of decreasing eigenvalues. The smallest principal components (which contribute least to the total variance) are then removed from $\mathbf{T}$, creating a reduced set of eigenvectors $\mathbf{T}^*$. For both PCR and PCR-S, principal components were retained which accounted for 95% of the total variance. A new dataset of orthogonal predictor variables $\mathbf{Z}$ can be constructed by transforming the original dataset:

$$\mathbf{Z} = \mathbf{X}\mathbf{T}^* \quad (4)$$

The relationship between the observed responses $\mathbf{y}$ and the transformed predictor variables $\mathbf{Z}$ becomes:

$$\mathbf{y} = \mathbf{Z}\boldsymbol{\alpha} + \boldsymbol{\varepsilon} \quad (5)$$

where $\boldsymbol{\alpha}$ is a vector of transformed regression coefficients. Similar to multiple linear regression, the regression coefficients can be calculated by using least squares regression such that:

$$\hat{\boldsymbol{\alpha}} = (\mathbf{Z}'\mathbf{Z})^{-1}\mathbf{Z}'\mathbf{y} \quad (6)$$

The muscle parameters $\boldsymbol{\beta}$ (i.e., regression coefficients in the original predictor variable space) can then be determined by:

$$\hat{\boldsymbol{\beta}} = \mathbf{T}^* \hat{\boldsymbol{\alpha}} \quad (7)$$

Note that although $\mathbf{T}^*$ is a reduced set of eigenvectors, $\boldsymbol{\beta}$ is an $m \times 1$ vector of regression coefficients.

Data concatenation

For the methods of MR and PCR, three-axis moment data from the ramp contractions of the 6 shoulder actions were used to determine muscle parameters. The entire arrays of internal shoulder moment data were concatenated for the 6 actions, and were subsequently concatenated a second time and arranged in the order of shoulder internal/external rotation, flexion/extension, and abduction/adduction moments, resulting in the vector $\mathbf{y}$ (Equation 1). EMG data were arranged in a similar fashion, such that the entire data arrays of EMG measurements were initially concatenated for the 6 shoulder actions. In this case though, the EMG measurements were individually weighted by the muscle moment arms for all three axes of the shoulder, resulting in three muscle moment arm-weighted EMG measurement matrices. These three matrices were then concatenated to correspond to the internal shoulder moment data, and this data comprised $\mathbf{X}$ (Equation 1). An illustration of this data concatenation process for MR and PCR is shown in Figure 2. Muscle moment arms were determined using Software for Interactive Musculoskeletal Modeling (Musculographics, Santa Rosa, CA, USA) and the Holzbaur shoulder model (Holzbaur et al., 2005).

For PCR-S, muscle parameters were computed in a sequential manner using single-axis moment data and EMG measurement data where muscles were associated with actions for

which they primarily contribute. Single-axis moment data consisted of the primary moment for the action which the subject was instructed to perform. Agonist and antagonist actions (e.g., abduction and adduction) were paired together in order to reduce multicollinearity. The entire data arrays of single-axis moment data for these paired actions were concatenated and comprised $\mathbf{y}$. EMG measurements were weighted by the muscle moment arms of the respective actions, and the entire data arrays of the muscle moment arm-weighted EMG measurement data for the paired actions were concatenated and comprised $\mathbf{X}$. Muscle parameters were sequentially determined in the following order: (1) elbow flexors/extensors, (2) shoulder adductors/abductors, (3) internal/external rotators, (4) and shoulder flexors/extensors. Figure 3 illustrates the data concatenation process for PCR-S for each of the four action pairs.

To clarify and expand on the methodology of PCR-S, muscle parameters for the elbow flexors/extensors were computed from the elbow flexion and extension trials using single-axis moment data (elbow flexion/extension moment data was used in place of internal shoulder moment data) and EMG measurement data from the three elbow flexor/extensor muscles. After determining muscle parameters for the elbow flexor/extensor muscles, muscle parameters for the shoulder adductor/abductor muscles were computed from the adduction and abduction trials using the adduction/abduction internal shoulder moment data and EMG measurement data from all muscles; internal shoulder moment data were first adjusted to account for the moment produced by all previously determined muscles (elbow flexors/extensors in this case). This procedure was then repeated for the shoulder internal/external rotators and finally the shoulder flexors/extensors. Muscles were associated with an agonist-antagonist action pair based on their largest moment arm in the calibration posture and were grouped as follows (abbreviations correspond to Figures 2 and 3): elbow flexors/extensors included the long (LHB) and short (SHB) heads of biceps and the long head of triceps (Tri); shoulder adductors/abductors include the middle deltoid (MDelt), suprapinatus (Supra), the sternocostal (StPec) and clavicular (ClPec) heads of pectoralis major, and the latissimus dorsi (Lat); internal/external rotators included the subscapularis (Subsc) and the infraspinatus (Infra); shoulder flexors/extensors included the anterior (ADelt) and posterior (PDelt) deltoids.

Evaluation of muscle parameter estimation methods

The three muscle parameter estimation methods were evaluated using three criteria in rank order: (1) the sign of the muscle parameters (signifying a positive or negative relationship between EMG and muscle force), (2) the standard deviation of the muscle parameters, and (3) the root mean square (RMS) error between the measured and the muscle parameter-predicted shoulder moments. Muscle parameters relate EMG to muscle force and should be positive when used to estimate physiologic (i.e., tensile) muscle forces. A student *t*-test was performed for each muscle and method to determine if each average muscle parameter was different from zero. Moreover, a test of proportions was used to determine if method affected the fraction of subjects yielding useful (i.e., all positive) parameter estimates (Fliess, 1981). In order to assess the variability of the muscle parameters for each method, a one-way ANOVA was performed on the standard deviations of the muscle parameters and *post hoc* Bonferroni tests identified differences between methods for each muscle. In addition, to determine the ability of a method to predict muscle parameters that produce joint moment, we assessed the product of the muscle moment arm (about each of the three axes) and standard deviation of the estimated muscle parameters. The RMS error is a measure of the accuracy of the predicted muscle parameters and was calculated using the mean, over all ramp contractions and subjects, of the Euclidean norm of the three-axis shoulder moments. A one-way ANOVA model was also used to determine if method affected RMS error with *post hoc* Bonferroni tests for each internal shoulder moment. A significance level of 0.05 was used, and all statistics were performed using SPSS (SPSS Inc., Chicago, IL, USA).

Results

Muscle parameters calculated using all three methods were found to be statistically different than zero ($p < 0.05$), except for the clavicular head of the pectoralis major and the triceps when calculated using MR. It was found that the muscle parameter estimation method did affect the fraction of subjects with usable muscle parameters ($p < 0.05$); Figure 4 shows the number of subjects with usable muscle parameters. Muscle parameters calculated using PCR-S yielded the greatest number of subjects with at least one set of trials with all positive muscle parameter estimates. The total percentage of positive parameter estimates for each method was 95.7 (SD 4.2), 91.0 (SD 7.3), and 86.3 (SD 8.8) for PCR-S, PCR, and MR, respectively. Although these percentages are relatively similar, MR and PCR often produced negative parameter estimates for one or a couple of muscles for each of the 3 sets of trials. The negative muscle parameters discounted the use of the associated set of trials for the prediction of muscle forces, thus reducing the number of subjects with usable muscle parameters with respect to PCR-S. The average condition number of the correlation matrix used to compute muscle parameters for PCR was 82.2 which implies that multicollinearity could be a source of error when using MR and supports the use of PCR and PCR-S (Belsley et al., 1980).

It was found that the estimation method affected the variability in the muscle parameters for the long and short heads of the biceps, the posterior deltoid, and the triceps ($p < 0.05$); Table 1 shows the average standard deviation of the muscle parameters, over all subjects, for each method. Weighting the variability of the muscle parameters by the moment arms (for each axis) yielded the same results.

There were statistically significant differences in the RMS error between the three methods ($p < 0.05$) (Figure 5). The differences in the RMS errors for the three methods can, in part, be attributed to the number of sets of trials with all positive muscle parameters and the data with which muscle parameters were computed. Predicted moments are only relevant when all muscle parameters are positive; MR and PCR yielded considerably fewer sets of trials with all positive muscle parameters with 6 and 12, respectively, of the 39 total sets of trials for all subjects, whereas PCR-S yielded 24. Muscle parameters computed using MR and PCR used data consisting of three-axis shoulder moments whereas PCR-S used data consisting of the primary, single-axis, internal shoulder moment for each action, thus muscle parameters were computed from only a subset of the data for PCR-S. Figure 6 shows an example of the measured and predicted shoulder moments using muscle parameters calculated using PCR-S for concatenated ramp contractions of external and internal rotation.

Discussion

We evaluated three methods for determining muscle parameters, relating EMG measurements to muscle forces, for the shoulder using a sub-maximal contraction protocol based on the sign and the standard deviations of the muscle parameter estimates and the RMS error between the measured and predicted internal shoulder moments. It was found that while PCR-S yielded the greatest number of subjects with usable (i.e., positive) muscle parameters and most consistently had the lowest variability in the muscle parameters, MR produced muscle parameters that yielded the best prediction of the measured shoulder moments; PCR produced muscle parameters that yielded results which fell between those of PCR-S and MR. However, it is important to note that the RMS error is only relevant when all muscle parameter estimates are positive. Thus, the selection of one muscle parameter estimation method is dependent on the evaluation parameter (i.e., parameter sign, variability, RMS error) of greatest importance such that there is a trade off between evaluation parameters. For example, if one would like to most often be able to predict *in vivo* muscle forces with less importance with regards to RMS error, PCR-S should be used as it most often produced positive muscle parameters. Likewise, if one

would like to most accurately predict internal shoulder moments, perhaps at the expense of more frequent negative, and thus unusable, muscle parameters, MR should be used.

The sign of the muscle parameters was of primary importance because positive muscle parameter estimates are necessary to predict tensile muscle forces. Stable muscle parameter estimates with lower standard deviations are important and indicate greater confidence in the determined parameters. Variations in the muscle parameters can be attributed to intra-action and inter-trial variations in muscle activation patterns. Although the results of the RMS errors between the predicted and measured moments suggest that PCR-S does not perform well, this result alone does not provide adequate information for evaluating the three muscle parameter calculation methods.

Muscle parameter estimation methods are limited by a number of assumptions. The EMG-muscle force relationship has been found to be relatively linear for sub-maximal contractions (Perry and Bekey, 1981) which supports the use of a sub-maximal calibration protocol. Sub-maximal protocols are important in the study and clinical treatment of pathologies, such as rotator cuff tears, post-surgical rehabilitation, or other conditions for which maximal contractions may cause further injury or damage. In the current study, maximal contractions were used to estimate each subject's 50% strength cutoffs. However, for pathologic populations, patient strength can be predicted based on age, gender, and weight (Hughes et al., 1999). Safe, sub-maximal, and subject-specific contraction levels could then be estimated using predicted MVC values in order to invoke sufficient muscle activity for use with the muscle parameter estimation methods used in the current study. For the current study, the muscle parameter estimation methods rely on the linearity or the correlation between EMG measurements and muscle forces, and do not require EMG normalization which relies on absolute and relative magnitudes of EMG measurements. Thus, error between a subject's measured 50% MVC and their true 50% MVC does not compromise the parameter estimation methods. EMG studies are prone to a number of weaknesses including assumptions of zero EMG signal with zero muscle force and that there is no cross-talk between electrodes. However, until better methods are developed, EMG is suitable for studying muscle activity. The muscle moment arms used in the calculations were obtained from a computational model developed using average population data, thus muscle moment arms are dependent on the ability of the model to accurately reproduce the shoulder anatomy in the postures of interest. In addition, muscle moment arms vary among individuals and these variations can influence the calculated internal shoulder moments used to compute muscle parameter estimates.

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Figure 1.
Experimental setup showing EMG electrodes and casted arm affixed to load cell.

Figure 2.

Data concatenation methods for MR and PCR. Internal shoulder moment (a) and processed EMG (b) data were first concatenated for 1 trial each of the 6 calibration actions. These data sets were subsequently concatenated by internal shoulder moment in the order of: internal/external rotation, shoulder flexion/extension, adduction/abduction; however EMG data were weighted by the muscle moment arms (R_{rot} , R_{flex} , and R_{add}) prior to the second concatenation. All muscle parameters for MR and PCR were estimated using the concatenated data sets of internal shoulder moments ($\mathbf{y}_{MR,PCR}$) and muscle moment arm-weighted EMG data ($\mathbf{X}_{MR,PCR}$) which correspond to the observed responses and predictor variables, respectively. Internal rotation, shoulder flexion, and adduction were defined as positive. Action abbreviations: ER: external rotation; IR: internal rotation; Flex: shoulder flexion; Ext: shoulder extension; Abd: abduction; Add: adduction. See Methods section (Data handling) for muscle abbreviations.

Figure 3.

Data concatenation process for PCR-S. Moment and EMG data were concatenated for agonist-antagonist actions; EMG data were weighted by the corresponding action muscle moment arms ($R_{elbow\ flex}$, R_{add} , R_{rot} , or R_{flex}). Muscle parameters for each set of action-associated muscle group were estimated using moments and muscle moment arm-weight EMG data, respectively, as follows: (a) elbow flexion/extension muscle used $\mathbf{y}_{PCR-S, elbow\ flex}$ (elbow flexion moment) and $\mathbf{X}_{PCR-S, elbow\ flex}$ for the three elbow muscles only; (b) adduction/abduction muscles used $\mathbf{y}_{PCR-S, add}$ and $\mathbf{X}_{PCR-S, add}$ for all 12 muscles; (c) shoulder internal/external rotation muscles used $\mathbf{y}_{PCR-S, rot}$ and $\mathbf{X}_{PCR-S, rot}$ for all 12 muscles; (d) shoulder flexion/extension muscles used $\mathbf{y}_{PCR-S, flex}$ and $\mathbf{X}_{PCR-S, flex}$ for all 12 muscles. Elbow flexion, adduction, internal rotation, and shoulder flexion were defined as positive. Action abbreviations: Elbow flex: elbow flexion; Elbow ext: elbow extension; Abd: abduction; Add: adduction; ER: external rotation; IR: internal rotation; Flex: shoulder flexion; Ext: shoulder extension. See Methods section (Data handling) for muscle abbreviations.

Figure 4.
Number of subjects with at least 1 set of trials with positive muscle parameters for all muscles.

Figure 5.

Average RMS error between the measured and predicted shoulder moments for sets of trials with all positive muscle parameters ($p < 0.05$); RMS errors were averaged over all motions and subjects for each method. Error bars represent one standard deviation.

Figure 6.

Example of measured (solid) and predicted (dashed) internal shoulder moments for ramp contractions of external and internal rotation, respectively. Although humeral rotations were the intended action, non-primary moments of abduction-adduction and shoulder flexion-extension were consequently produced; this was consistent for all subjects. Adduction, internal rotation, and shoulder flexion are positive.

Table 1

Average muscle parameter standard deviations, over all subjects, for each parameter estimation method.

Muscle	Parameter estimation method		
	MR	PCR	PCR-S
Sternocostal pectoralis	1079.31	870.40	602.07
Clavicular pectoralis	1401.23	1152.61	715.91
Long head of biceps ^{a,b}	3905.18	1174.84	96.00
Short head of biceps ^{b, c}	1154.47	864.35	109.27
Anterior deltoid	1097.57	489.84	800.13
Middle deltoid	287.78	323.60	288.48
Posterior deltoid ^c	502.65	391.13	1549.69
Infraspinatus	2082.66	1678.30	1736.17
Long head of triceps ^{a,b}	7473.55	2294.16	727.28
Latissimus dorsi	2945.44	1680.95	3695.84
Supraspinatus	1441.67	1021.39	408.36
Subscapularis	1738.14	1485.46	4396.46

^a Statistical differences between methods (p<0.05) indicated by: (MR vs. PCR)^b (MR vs. PCR-S), and^c (PCR vs. PCR-S).