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Muscle Recruitment Strategy for Musculoskeletal Modeling of the Shoulder

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Abstract: Musculoskeletal modeling software has the potential to open new pathways in biomechanics and human factors analysis and research. However, the output of these models is only as good as the model itself. Decisions made when setting up the model can drastically alter the results and output of the model. Musculoskeletal models rely on optimization algorithms, called muscle recruitment strategies, to determine muscle activity required to perform the modeled task. In this research, five participants were recruited to perform a static and dynamic task at 3 weight levels (2.5, 5, and 10 lbs) while upper body motion capture data and electromyography data of muscles driving the shoulder were collected. Each trial was modeled in AnyBody Musculoskeletal Modeling System with each of the six available recruitment strategies. Correlation analysis was performed between the electromyography data for each muscle and the corresponding muscle activity output of the musculoskeletal model to determine which muscle recruitment strategy resulted in the most accurate reproduction of the muscle activity of the participants. Poly4 and Min/Max had the highest correlations for dynamic and static tasks, respectively.

Keywords: Musculoskeletal Modeling, Recruitment Strategies, Shoulder

1. Background and Introduction

Linked-segment models of the human body are commonly used to quantify forces, moments, and torques at the body joints to estimate the strain on the body. While linked-segment models are often used to estimate the resultant force at a joint, they neglect the internal body forces caused by action of the muscles. The shoulder, for instance, is completely wrapped in muscles, each with a different line of action that will influence the resultant force. Until recently, this was just an unavoidable limitation. However, the conception of musculoskeletal modeling software, such as AnyBody Modeling System 6.0 (AnyBody Technologies, Aalborg, DK), provides a pathway to avoid that limitation and opens doorways to new avenues of biomechanical analysis with improved accuracy over linked-segment models.

AnyBody Modeling System software utilizes a scaled musculoskeletal model with bones, joints, and muscle-tendon units that is capable of accounting for complex physiological properties during the analysis (AnyBody Tutorial, Chapter 5), making it much more robust and flexible than simple linked-segment models.

In the model, muscles are represented with musculotendon units. Optimization algorithms, called muscle recruitment strategies, are used to determine the activity of the musculotendon units that is required to perform the modeled task, i.e. to move the body to the posture fitting the motion capture markers at each timeframe, accounting for body weight, dynamic factors, and external forces. In most cases, multiple musculotendon units are used to represent a single muscle to more accurately represent the muscles (Figure 1). Muscle activity in the model is computed as the percentage of the maximum force capability of the musculotendon unit that was used to perform the task being modeled based on the optimization results for the selected muscle recruitment strategy. The maximum force capability of each musculotendon unit is determined by multiplying a set strength factor (115 N/cm^2) by the cross-section of the musculotendon unit. Musculotendon unit cross-section, along with body segment lengths and masses, are scaled based on the height and weight of the modeled participant.

Since the outputs of the model depend heavily on the muscle activity, it's important to use the muscle recruitment strategy that results in muscle activity that most closely resembles the muscle activity of the modeled participant while performing the modeled task. The available muscle recruitment strategies in AnyBody modeling software are linear, quadratic, polynomial, min/max, and composite muscle recruitment strategies that rely on optimization. Linear, quadratic, and polynomial muscle recruitment minimize Equation 1, where the value for p determines muscle recruitment pattern. Composite muscle recruitment uses a similar form, however with minimization of a quadratic term and an additional, weighted, linear term

(Equation 2). Finally, min/max muscle recruitment minimizes the maximal muscle activity using an internal algorithm represented in Equation 3.

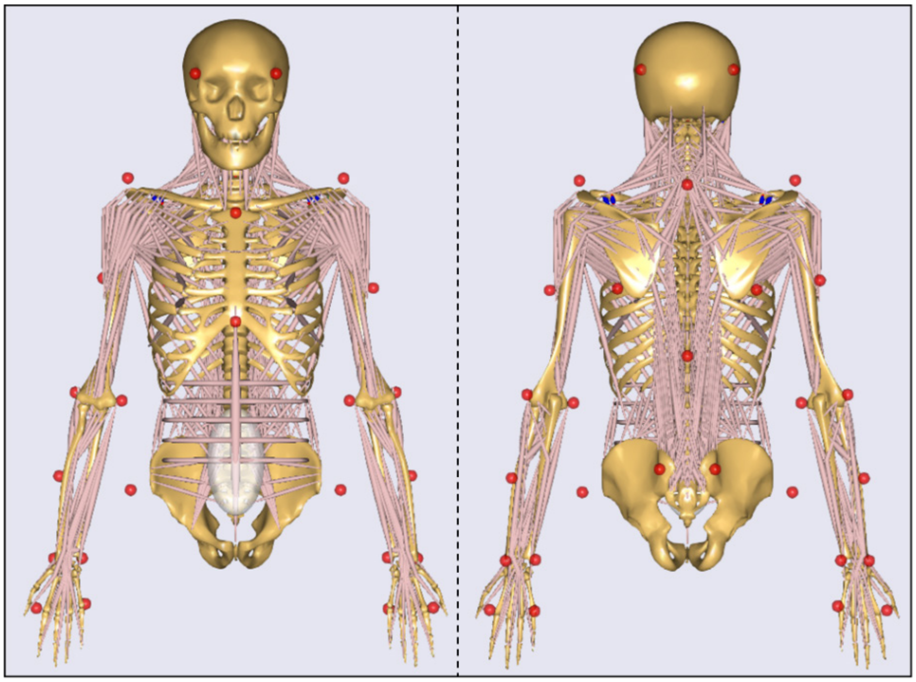

Figure 1. Upper body model with musculotendon units visible.

$$G = \sum_i \left(\frac{f_i}{N_i}\right)^p, \text{ p} = 1,2,\ldots\text{n} \tag{1}$$

where:

p = 1 for linear,
p = 2 for quadratic, and
p = 3 or more for polynomial.

$$G = \sum_i \left(\frac{f_i}{N_i}\right)^2 + x\left(\frac{f_i}{N_i}\right) \tag{2}$$

where x = (0,1).

$$G = \max\left(\frac{f_i}{N_i}\right) \tag{3}$$

Linear muscle recruitment will recruit the fewest muscles possible to perform the action, beginning with the strongest muscle. Linear muscle recruitment is not physiologically realistic, however. Quadratic muscle recruitment is much more physiologically appropriate, allowing synergism between muscles by penalizing large terms. Polynomial muscle recruitment with power p = 3 shows increased muscle synergism, with muscle synergism further increasing as the power of the equation increases. As the power of the polynomial muscle recruitment algorithm nears infinity, the algorithm becomes less numerically attractive and requires upper bound constraints to be specified. The min/max recruitment strategy converges with the polynomial muscle recruitment algorithm for large values of p, is more numerically attractive due to reduction to one equation with one unknown and implicitly fulfills the upper bounds constraints for sub-maximal loads due to maximizing muscle synergism (Rasmussen et al. 2001). However, maximizing muscle synergism results in exploitation of muscles with small moment arms that may not be realistic (Forster, 2003).

2. Methods

2.1 Participants

A convenience sample of five healthy, male participants with mean age, height, and weight of 25.6 (±3.8), years, 1.76 (±0.03) meters, and 70.3 (±8.5) kg, respectively, were recruited from a university population for this research. For inclusion in the study, potential participants had to be male, aged 18-40 years old, right-hand dominant, and have no musculoskeletal disorders that would affect their ability to perform the tasks or that could otherwise affect the results.

2.2 Equipment

Motion Capture System (Vicon Motion Systems, Oxford, UK): An eight-camera optical motion capture system was used to record the motion of the upper body of the participants while performing the experimental tasks. Spherical 12mm retroreflective markers were tracked at a rate of 100Hz using infrared light emitted and captured with the cameras.

Electromyography System (Bagnoli-16, Delsys Inc., Natick, MA, USA): A 16-channel electromyography system and surface electromyography sensors were used to capture the muscle activity from upper body muscles during the experimental tasks at a rate of 1000Hz.

2.3 Participant Preparation

Upon arrival, recruited participants were introduced to the experimental setup and tasks, signed consent forms approved by the local Institutional Review Boar, and retroreflective markers and electromyography sensors were applied. Electromyography sensors were placed on the Anterior, Middle, and Posterior Deltoid, Clavicular, Sternal, and Abdominal branches of the Pectoralis Major, the Lateral and Medial branches of the Biceps Brachii, Tricep, Latissiumus Dorsi, Infraspinatus, Supraspinatus, and Teres Major according to placements specified by Criswell and Cram (2011), SENIAM, Krol (2007), and Xu et al. (2014).

Participants performed three repetitions of each of 7 Maximum Voluntary Contraction (MVC) tasks designed to maximally exert one or more of the muscles whose activity is being recorded with electromyography. A rest period of 2 minutes was provided between exertions. The results from these trials were used to normalize the electromyography data collected during the experimental tasks. Subsequently, thirty-two (32) retroreflective markers were affixed to anatomical landmarks (Table 1) on the participants upper body and pelvis using double-sided tape.

Table 1. List of 32 retro-reflective markers in the marker set and their locations on the body.

Head		**Pelvis**	
RFHD/LFHD	Right/left side of forehead	RASI/LASI	Right/left anterior iliac spine
RBHD/LBHD	Right/left side of back of head	RPSI/LPSI	Right/left posterior iliac spine
Trunk			
C7	Spinous process of C7 vertebrae	STRN	Xiphoid process at base of sternum
CLAV	Sternal notch at top of sternum	T10	Spinous process of T10 vertebrae
RSHO/LSHO	Right/left acromion process of shoulders	RBAK/LBAK	Inferior angle of right/left scapula
Left/Right Arms			
RUPA/LUPA	Midpoint of right/left upper arm on lateral side	RWRA/LWRA	Radial styloid of right/left wrist
RLELB/LLELB	Lateral epicondyle of humerus at right/left elbow	RWRB/LWRB	Ulnar styloid of right/left wrist
RMELB/LMELB	Medial epicondyle of humerus at right/left elbow	RFIN/LFIN	5th MCP joint of right/left hand
RFRM/LFRM	Midpoint of right/left forearm	RTHB/LTHB	2nd MCP joint of right/left hand

2.4 Experimental Tasks

A single experimental task with 3 weight conditions (2.5, 5, and 10 pounds) was used in this research. Participants began with the weight in their right hand with their arm straight and to the side. When prompted to begin, the participant lifted their right arm to the side until horizontal, while keeping the arm straight, over a period of three seconds. This posture was held for 5 seconds, then the participants set down the weight. Three repetitions with each weight were performed for a total of 9 experimental trials per participant.

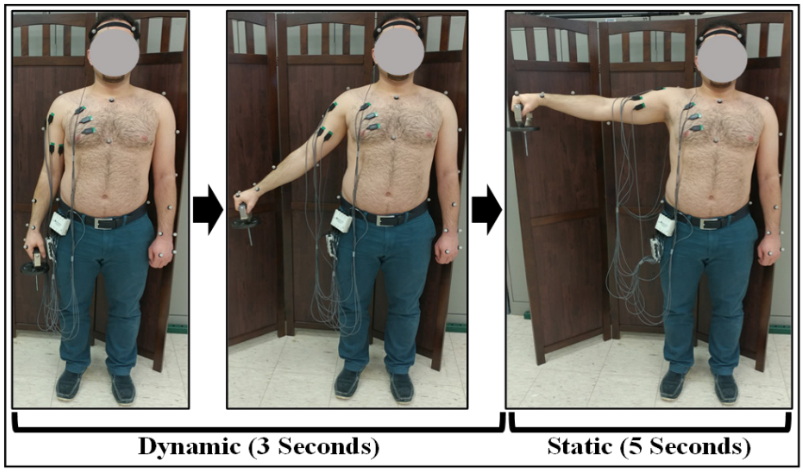

Figure 2. Progression for the experimental task performed by the participants. Participant is lifting a 2.5 pound weight.

2.5 Data Processing

2.5.1 Electromyography

Electromyography data for each MVC and experimental trial was demeaned, full-wave rectified, and low-pass filtered with a using a digital 4^{th} order Butterworth filter with a 4Hz cut-off to generate a linear envelope. For each participant, the peak values for each muscle across all MVC trials was used to normalize the linear envelopes for each experimental trial, resulting in frame-by-frame %MVC values. The data was down-sampled to 100Hz to match the sample rate of the motion capture and model output data.

2.5.2 Musculoskeletal Modeling

Trials were modeled in AnyBody Modeling System using the collected motion capture data to drive the movement of the model. Each trial was modeled six times, using each of the 6 muscle recruitment strategies. Frame-by-frame muscle activity (MA%) was output for each modeled trial.

2.6 Analysis

Electromyography (%MVC) and Muscle Activity Percentage (MA%) output from the model were split into their static and dynamic portions. For the dynamic portion of the task, RMSE and Pearson correlation analysis were performed between the %MVC and MA% values. Since the muscle activity of the static portion of the tasks will be largely stagnant, calculating Pearson correlation is not feasible, as correlation values nearing 1 would be expected for all trials. Instead, spearman rank correlation was used to determine how closely the contribution of each muscle matches between the MA% and %MVC values. The total force exerted by all muscles together was calculated by multiplying the %MVC and %MA values by the maximum force capability values for each muscle. The total force exerted by each muscle was divided by the total maximum force capability of all 13 muscles combined to determine the proportion that each muscle contributed to the total overall force. For each recruitment strategy, Spearman Rank Correlation values were calculated between the 13 proportion values calculated from the electromyography data and 13 proportion values calculated from the model output data.

2.6.1 Dynamic Analysis

Mean correlation for each recruitment strategy across all muscles and weight conditions ranged from 0.4939 to 0.5643 for the MMS and Poly4 strategies, respectively. Corresponding RMSE values ranged from 0.1458 to 0.1669 for MMS and Quad strategies, respectively (Table 2). Based on this analysis it appears that Poly4 resulted in the highest mean correlation, while maintaining a relatively low mean RMSE value (Figure 3).

Table 2. Overall mean correlation and RMSE values for each recruitment strategy for the dynamic analysis.

Recruitment Strategy	Correlation	RMSE (%)
Quadratic (Quad)	0.5146	0.1669
3rd-order Polynomial (Poly3)	0.5621	0.1599
4th-order Polynomial (Poly4)	0.5643	0.1544
5th-order Polynomial (Poly5)	0.5353	0.1514
Min/Max (MMS)	0.4939	0.1458
Composite (Comp)	0.5300	0.1661

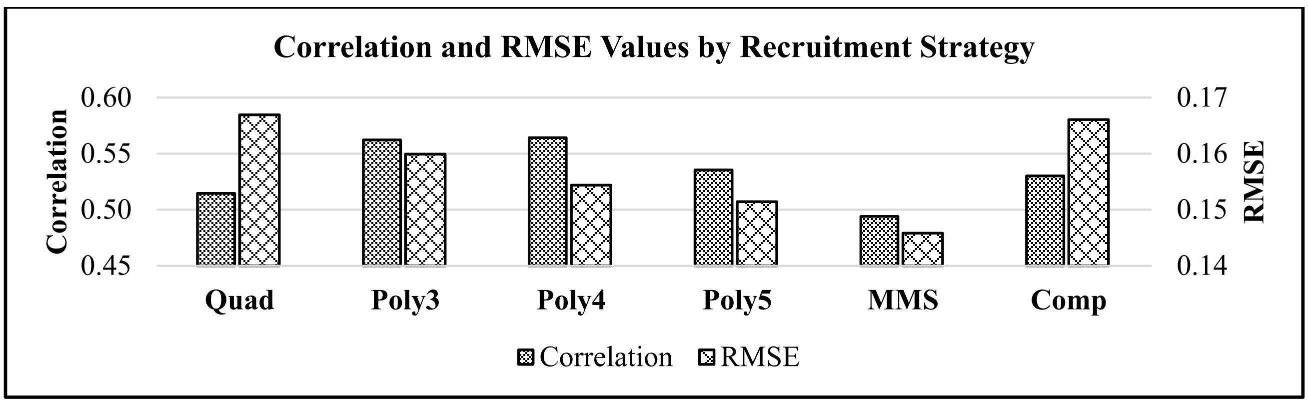

Figure 3. Mean correlation values and mean RMSE values found for each recruitment strategy for the dynamic analysis.

2.6.2 Static Analysis

Mean correlations for each recruitment strategy across all weights ranged from 0.7338 for the Composite strategy up to 0.8072 for the Min/Max strategy. Corresponding RMSE values ranged from 0.0235 for the Mix/Max Strategy up to 0.0258 for the Quadratic Strategy (Table 3). The MMS recruitment strategy showed the highest correlation values and the lowest RMSE values of the recruitment strategies (Figure 4). The RMSE values in this case are very low, suggesting that the proportional contributions of each muscle remain relatively consistent across all recruitment strategies.

Table 3. Overall mean correlation values and mean RMSE values for each recruitment strategy for the static analysis.

Recruitment Strategy	Correlation	RMSE (%)
Quadratic (Quad)	0.7492	0.0258
3rd-order Polynomial (Poly3)	0.7408	0.0250
4th-order Polynomial (Poly4)	0.7558	0.0245
5th-order Polynomial (Poly5)	0.7771	0.0242
Min/Max (MMS)	0.9072	0.0235
Composite (Comp)	0.7338	0.0255

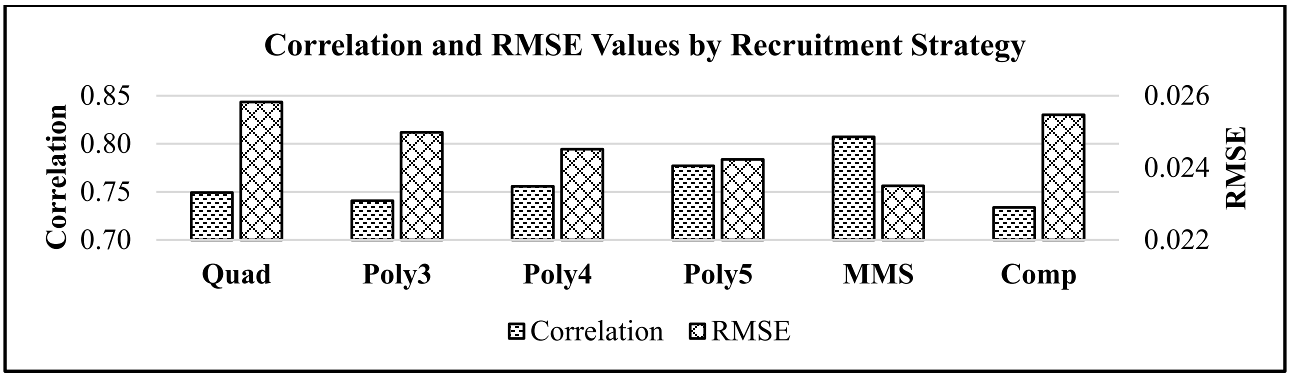

Figure 4. Mean correlation values and mean RMSE values found for each recruitment strategy for the static analysis.

3. Discussion & Conclusions

Muscle recruitment strategies in AnyBody Modeling System were compared using motion capture and electromyography data with a focus on the shoulder. Poly4 and MMS were found to be the most accurate muscle recruitment strategies for dynamic and static postures, respectively, based on comparisons with electromyography data. However, comparison with the electromyography data proved difficult. First, the larger muscles in the body are represented by multiple musculotendon units that each provide a different result for muscle activity. Making comparisons between one number and multiple non-independent values is a challenge, statistically. Additionally, since the muscle activity is computer generated, it does not have the same sinusoidal characteristics as the electromyography data. However, this is novel research, and no existing, verified, or accepted methods exist for this comparison. This research provides evidence supporting the use of these recruitment strategies for modeling of the shoulder.

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