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An EMG-assisted model calibration technique that does not require MVCs

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ABSTRACT

As personalized biologically-assisted models of the spine have evolved, the normalization of raw electromyographic (EMG) signals has become increasingly important. The traditional method of normalizing myoelectric signals, relative to measured maximum voluntary contractions (MVCs), is susceptible to error and is problematic for evaluating symptomatic low back pain (LBP) patients. Additionally, efforts to circumvent MVCs have not been validated during complex free-dynamic exertions. Therefore, the objective of this study was to develop an MVC-independent biologically-assisted model calibration technique that overcomes the limitations of previous normalization efforts, and to validate this technique over a variety of complex free-dynamic conditions including symmetrical and asymmetrical lifting. The newly developed technique (non-MVC) eliminates the need to collect MVCs by combining gain (maximum strength per unit area) and MVC into a single muscle property (gain ratio) that can be determined during model calibration. Ten subjects (five male, five female) were evaluated to compare gain ratio prediction variability, spinal load predictions, and model fidelity between the new non-MVC and established MVC-based model calibration techniques. The new non-MVC model calibration technique demonstrated at least as low gain ratio prediction variability, similar spinal loads, and similar model fidelity when compared to the MVC-based technique, indicating that it is a valid alternative to traditional MVC-based EMG normalization. Spinal loading for individuals who are unwilling or unable to produce reliable MVCs can now be evaluated. In particular, this technique will be valuable for evaluating symptomatic LBP patients, which may provide significant insight into the underlying nature of the LBP disorder.

1. Introduction

Electromyography (EMG) has emerged as an essential tool for evaluating personalized tissue loading in the trunk (Marras and Mirka, 1990; Granata and Marras, 1993, 1995b; Marras and Granata, 1997a). Since raw EMG signals are difficult to interpret (Lehman and McGill, 1999), most EMG-assisted models of the trunk normalize myoelectric data relative to maximum voluntary contractions (MVCs) (McGill and Norman, 1986; Marras and Sommerich, 1991a; Granata and Marras, 1993; Cholewicki et al., 1995; Gagnon et al., 2001; van Dieen et al., 2003; Staudenmann et al., 2010). However, true MVCs are difficult to obtain (Korkmaz et al., 2006; Splittstoesser et al., 2007) and can be sensitive to sincerity of effort, fatigue, training (Baratta et al., 1998), posture (Mirka, 1991), exertion type (Ng et al., 2002; Vera-Garcia et al., 2010), and pain on exertion (Keller et al., 1999). These sensitivities introduce significant variability that can inhibit the MVC from being a reliable normative measure within and across subjects. In addition to sensitivity issues, the large forces that are experienced during MVCs can be uncomfortable and may expose subjects to injury risk (Zeh et al., 1986; Battié et al., 1989). As a result, symptomatic low back pain (LBP) patients are generally unable or unwilling to perform MVCs and, thus, cannot be accurately evaluated by most EMG-assisted models.

Some EMG-assisted modeling efforts have attempted to predict MVCs experimentally in order to eliminate the need to measure them. One group reported a technique for predicting MVCs based on sub-maximal exertions and anthropometric regressions (Marras and Davis, 2001; Marras et al., 2001a). These regressions, however, explained only a small portion of the variability associated with MVCs. Others have predicted MVCs in combination with maximum muscle stress properties (Cholewicki et al., 2011), but resulted in maximum muscle stress predictions that fell outside the physiological range 31% of the time. In addition, neither of these normalization techniques was evaluated free-dynamically or in multiple planes simultaneously and, thus, their effects during realistic loading conditions may not be fully understood. Therefore, the objective of this study was to develop an MVC-independent biologically-assisted model calibration technique that overcomes the limitations of previous MVC-based and MVC-independent normalization efforts, and to validate this technique over a variety of complex free-dynamic conditions including symmetrical and asymmetrical lifting.

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2. Calibration hypothesis

The biologically-assisted model used in this study utilizes personal kinematic, kinetic, and biological (EMG) information about the trunk to predict the three-dimensional loads and moments that are imposed on the lumbar spine during free-dynamic exertions. Unlike traditional models which have only assessed spinal loads at a single intervertebral level, this model outputs predicted peak compression, anterior–posterior shear, and lateral shear spinal loading at the endplates of each of the six lumbar intervertebral discs from T12-L1 to L5-S1. The underlying logic, history, and validation of this model are well-established (Marras and Sommerich, 1991a,b; Granata and Marras, 1993,1995a; Marras and Granata, 1995, 1997a,b; Theado et al., 2007; Knapik and Marras, 2009).

The model calculates spinal loads as reactions to body segment kinetics, externally applied loads, and muscle-generated moments. Three-dimensional muscle-generated moment (M) predictions (Eq. (1)) are made by dynamically summing vector products between tensile forces (F) and moment arms (r) for each of the 10 model muscles (j). Model muscles include bilateral erector spinae, latissimus dorsi, rectus abdominis, internal oblique, and external oblique pairs.

$$\vec{M} = \sum_{j=1}^{10} \vec{r}_j \times \vec{F}_j \tag{1}$$

2.1. Established MVC-based model calibration technique

Traditionally, dynamic tensile forces for each muscle (j) have been predicted (Eq. (2)) as the product of muscle gain (maximum muscle strength per unit area), normalized EMG, muscle cross-sectional area, and modulation factors describing the force–length and force–velocity relationships of skeletal muscle.

$$F_j(t) = \text{Gain}_j \cdot \frac{\text{EMG}_j(t)}{\text{MVC}_j} \cdot \text{Area}_j \cdot f[L_j(t)] \cdot f[v_j(t)] \tag{2}$$

With this approach, dynamic myoelectric activities ($\text{EMG}_j(t)$) are normalized to maximum voluntary contractions (MVC_j). Personalized cross-sectional areas (Area_j) are represented to account for known size effects on muscle force generating capacity and are calculated directly from MRI or from MRI-based regressions (Marras et al., 2001b). Length ($f[L_j(t)]$) and velocity ($f[v_j(t)]$) dependent force modulation curves have been derived experimentally (Theado et al., 2007). Personalized muscle gains (Gain_j) are calculated for all 10 model muscles via a constrained nonlinear multivariable optimization algorithm which minimizes error in predicted internal moments relative to measured external moments in three physiological planes during free dynamic calibration exertions. This algorithm ensures that gains fall within the physiological range of 30–100 N/cm^2 (Close, 1972; Weis-Fogh and Alexander, 1977; Reid and Costigan, 1987; McGill and Norman, 1987), and has been adapted from previous works (Marras et al., 2009).

2.2. New non-MVC model calibration technique

The new non-MVC model calibration technique eliminates the need to measure MVCs by defining a new muscle property called "gain ratio" (GR_j). This muscle property combines Gain_j and MVC_j into a single personalized muscle property (Eq. (3)) that can be determined during calibration. In order to account for the variety of hardware gains that are utilized by EMG systems, signals are software gained to mimic a standard hardware gain of 10,000. Therefore, the gain ratio defined here is in fact muscle gain divided by muscle MVC if the MVC were recorded with a hardware gain of 10,000. Since the units of this property are rather complex (N/cm^2 V), they will be referred to as gain ratio units (GRU). With this technique, the same calibration procedure that has been established previously to determine gain can be used instead to determine gain ratio, and EMG normalization is intrinsically accounted for in the personalized gain ratio property. Since no physiological range of gain ratios were discovered, maximal and minimal values were determined experimentally.

$$\text{GR}_j = \frac{\text{Gain}_j}{\text{MVC}_j} \tag{3}$$

2.3. Model fidelity measures

Dynamic model fidelity is determined by comparing muscle-generated moment predictions to externally measured moments in both the sagittal and lateral physiological planes simultaneously. Axial plane moments are not considered since they are negligible compared to sagittal and lateral moments during free-dynamic lifting exertions at comfortable speeds. Multi-planar average absolute error (AAE) and r-squared (r^2) measures are used to quantify the fidelity of moment predictions during dynamic exertions and are calculated by summing single-planar AAE and r^2 measures that have been weighted relative to peak in-plane moments. AAEs were normalized to peak in-plane moments prior to weighting to facilitate intersubject comparability.

3. Methods

3.1. Approach

A study was conducted to develop and validate a new biologically-assisted model calibration technique that does not require MVCs for EMG normalization (non-MVC). An established MVC-based model calibration technique was used as the basis for comparison. The study consisted of three parts:

1. The determination of gain ratio limits to be used by the new model calibration technique.
2. The comparison of within subject gain ratio prediction variability between the new and established model calibration techniques.
3. The comparison of spinal load predictions and model fidelity between the new and established model calibration techniques when evaluating an independent test set of multi-planar torso exertions, as well as an independent test set of symmetrical and asymmetrical lifts.

The judgment criteria for the utility of the non-MVC model calibration technique required that it demonstrates the same or less within subject gain ratio prediction variability, predicts similar spinal loads, and exhibits as good or better model fidelity when compared to the established MVC-based technique.

3.2. Subjects

Ten subjects (five male, five female) participated in this study. This sample size was found to be sufficient for investigating the effects of interest with a power of .8 and a significance level (α) of .05. All subjects were asymptomatic for LBP and provided informed consent prior to study participation. Mean age, body mass, and stature of the subjects who participated in this study were 24.2 (2.1) years, 70.5 (10.1) kg, and 173.8 (9.1) cm, respectively.

3.3. Experimental design

3.3.1. Gain ratio limit determination

After calibrating each subject via the established MVC-based technique, gain ratios were calculated by dividing each muscle gain by its respective MVC (after software adjusting the MVC to a hardware gain of 10,000). Maximal and minimal values were then used to determine the gain ratio limits to be used by the new non-MVC model calibration technique.

3.3.2. Comparison of gain ratio prediction variability

A repeated measures experimental design was implemented to compare gain ratio prediction variability, with model calibration technique (either MVC-based or non-MVC) serving as the independent variable. For each subject, the biologically-assisted model was calibrated eight separate times throughout the study (four times with each of the model calibration techniques). Each calibration required the subject to perform six calibration exertions, from which the best three were selected based on model fidelity measures to calibrate the model. Calibration exertions required the subject to dynamically move his or her upper torso both sagittally and laterally through a comfortable range of motion at a comfortable pace while holding a 4.54 kg medicine ball close to the chest. These exertions were designed to elicit both concentric and eccentric activation from each of the 10 trunk muscles while producing measured moments in multiple planes so as to provide the calibration algorithms sufficient resolution.

As required by each MVC-based calibration, an independent set of MVCs was also collected. Sets of MVCs were each determined from the maximal myoelectric activity produced by each muscle during six maximal isometric exertions (sagittal flexion and extension, left and right lateral bends, and left and right twists) that were performed in a fixed reference frame. All maximal exertions were performed in the upright posture except for sagittal extensions, which were performed with the subject flexed forward 20° in the sagittal plane. Verbal encouragement was provided to the subject during maximal exertions, and a 2-min rest period was provided between each maximal exertion to minimize fatigue. Model calibration technique order was counterbalanced across subjects with the condition that neither technique be performed twice in a row. Within subject gain ratio coefficients of variation (standard deviation divided by mean) for each of the 10 model muscles served as dependent variables for evaluating gain ratio prediction variability.

3.3.3. Comparison of spinal load predictions and model fidelity

Two independent test sets were evaluated with each of the eight previously mentioned calibrations. Model calibration technique (either MVC-based or non-MVC) served as the primary independent variable of interest.

The first independent test set consisted of twelve multi-planar torso exertions, which were performed while holding a 4.54 kg medicine ball. Multi-planar torso exertions were similar to calibration exertions, but were collected independently.

The second independent test set consisted of symmetrical and asymmetrical lifts where three levels of load weight (either 0, 4.54, or 6.80 kgs) and five levels of load origin (either 60° counterclockwise, 30° counterclockwise, 0°, 30° clockwise, or 60° clockwise measured from the anterior portion of the sagittal plane) were varied. Each combination of load weight and load origin was repeated twice, resulting in a total of 30 lifts. Non-zero load weights were achieved by adding weight to a box with between handle width, handle diameter, and depth of 39, 3.2, and 28 cm, respectively. To maintain similar kinematics, the zero kg condition was performed with a cardboard replica box (.15 kg) with the same handle sizes and locations as the non-zero conditions. The axial radius of the load location relative to the subject's starting L5/S1 intervertebral joint position was set equal to the length of the subject's lower arm, and the height was set so that the handles were level with the proximal interphalangeal joint of the subject's middle finger when his or her arms were relaxed to the side. All lifts required the subject to retrieve the load without moving his or her feet and return to face forward with the box held close to the body and elbows at 90°.

All multi-planar torso exertions and lifts were performed at a comfortable pace, and were collected after the first two calibrations (one MVC-based and one non-MVC) had been performed. Compression, anterior–posterior shear, and lateral shear spinal load predictions at the superior endplate of each of the lumbar intervertebral discs as well as model validity measures served as dependent variables. Lift order was randomized with the condition that each experimental task be performed once before any combination was performed the second time.

3.4. Apparatus

Electromyography (EMG) data was collected with a Model 12 Neuradata Acquisition System (Grass Technologies, West Warwick, RI, USA) at a sampling rate of 1000 Hz. Signals were first high-pass filtered at 30 Hz, low-pass filtered at 450 Hz, and notch filtered at 60 Hz and corresponding aliased frequencies with a sideband of .25 Hz. The signals were then rectified and smoothed via a zero-phase moving average filter. An appropriately-sized Lumbar Motion Monitor was fitted to each subject to monitor trunk kinematics (Marras et al., 1992). Ground reaction forces were measured via a Bertec 4060A force plate (Bertec, Worthington, OH, USA). A Pelvic Angle Monitor and Moment Arm Monitor were used to track the location and orientation of each subject's L5-S1 intervertebral disc (Fathallah et al., 1997). Custom Laboratory Information Management System software developed at The Ohio State University Biodynamics Laboratory was used to collect all signals through a PCI-6031E Data Acquisition Device (National Instruments, Austin, TX, USA). SAS® statistics software was used for all statistical calculations.

3.5. Procedures

Subjects were given a brief description of the tasks they would be asked to perform. After providing informed consent, anthropometric measurements were collected and used as model inputs. Standard muscle site preparation guidelines were followed (Marras, 1990), and surface electrodes were applied to each of the 10 model muscles according to standard placement procedures (Soderberg, 1992; Mirka and Marras, 1993). Subjects were fitted with a Lumbar Motion Monitor, Moment Arm Monitor, and Pelvic Angle Monitor during all trials except maximum exertions. Experimenters demonstrated and allowed subjects to familiarize themselves with all exertions before they were recorded. Experimental tasks were performed according to the study design.

3.6. Statistical analyses

Statistical significance was determined by univariate analysis of variance (ANOVA) with a significance level (α) of .05. Main effects for each independent variable were investigated, and test statements were used to specify error terms. An additional statistical analysis was performed to investigate whether gender, load weight, or load origin interacted with model calibration technique during the independent test set of symmetrical and asymmetrical lifts. All tests were performed with subject as a blocking factor and gender nested within subject. Statistical results were interpreted relative to biomechanical and biological significance.

4. Results

4.1. Data quality

During experimental lifting tasks, two female subjects experienced frequent muscle activations that exceeded their maximum voluntary contractions (MVCs). This is a direct indication that these subjects produced unreliable MVCs. As a result, average AAE measures (31.0%) for these subjects were exceptionally poor when they were calibrated with the MVC-based technique, indicating unreliable gain ratio and spinal load predictions. Therefore, subsequent data relying on these subjects' MVCs were removed. It was not necessary to remove any data with the non-MVC model calibration technique.

For each of the remaining subjects, MVCs for each muscle were normalized relative to the maximum MVC produced by that muscle throughout the study. Normalized MVCs for a representative muscle in a subsample of representative subjects are shown in Fig. 1. Normalized MVCs observed in this study were 85.6% (13.6%) on average and reached as low as 42.7%. Similar findings were observed in the ground reaction force and ground reaction moment data collected during maximum exertions. Pearson correlation coefficients were generated to investigate order (time) effects on MVC output variables resulting from factors such as training and fatigue, none of which were significant.

4.2. Gain ratio limit determination

Mean gain, gain ratio, r^2, and AAE values for MVC-based model calibrations were 46.6 (13.8) N/cm^2, 44.8 (24.2) GRU, .80 (.04), and 10% (2%), respectively. Gains from this population ranged from 30.0 N/cm^2 to 91.7 N/cm^2. Normal probability plots indicated that predicted gain ratios were normally distributed. Maximal (131) and minimal (6) gain ratio limits were calculated from this population and were taken to represent the physiologically relevant range.

4.3. Comparison of gain ratio prediction variability

Similar average gain ratio prediction variability was observed between Non-MVC (13.7%) and MVC-based (15.1%) model calibration techniques. A comparison of within subject gain ratio coefficients of variation between model calibration techniques broken down by muscle is shown in Fig. 2. Differences in gain ratio prediction variability between model calibration techniques were found to be statistically significant only in the right erector spinae (p = .05).

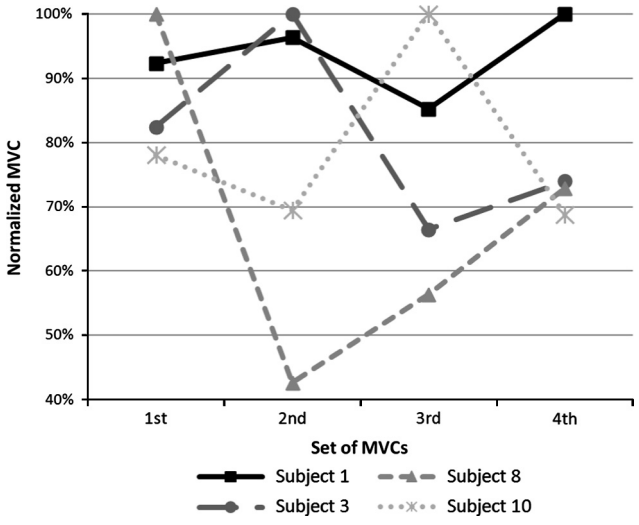

Fig. 1. Normalized MVCs taken throughout the study for a representative muscle (right erector spinae) in a subsample of representative subjects. Subjects 1, 3, and 8 were males, and subject 10 was female.

4.4. Comparison of spinal load predictions and model fidelity

No statistically significant differences in spinal loads were found between model calibration techniques for either of the independent test sets, though loads predicted by the non-MVC technique were consistently lower. Spinal loads for the independent test set containing symmetrical and asymmetrical lifts are shown in Fig. 3. Statistically significant interactions between model calibration technique and load origin were found for anterior–posterior shear loads at L5S1 (p = .03) and lateral shear loads from L2L3 to T12L1 (p = .02–.04), however differences between model calibration techniques within load origin for these measures were all less than 20 N. Therefore, these interactions were not found to be biomechanically or biologically significant.

No statistically significant differences in multi-planar r^2 (.81 vs. .81) or AAE (15.4% vs. 15.2%) model validity measures were found between the MVC-based and non-MVC model calibration techniques, respectively for either of the independent test sets. AAEs were equivalent to less than 8 N m in the sagittal plane and less than 10 N m in the lateral plane.

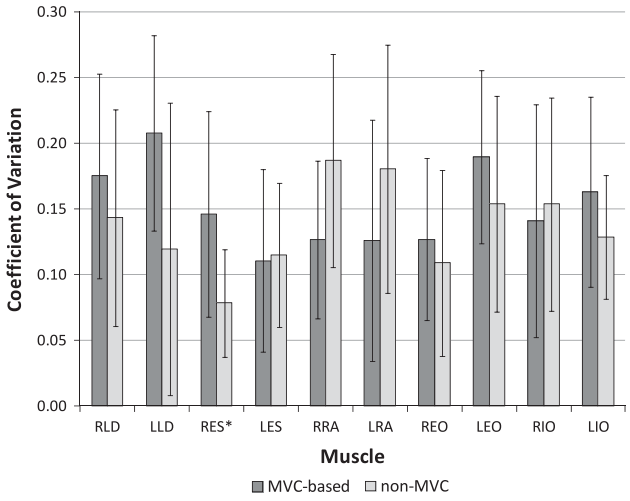

Fig. 2. Comparison of within subject gain ratio coefficients of variation between model calibration techniques for each of the 10 trunk muscles (RLD/LLD = Right/Left Latissimus dorsi; RES/LES = Right/Left Erector spinae; RRA/LRA = Right/Left Rectus abdominis; REO/LEO = Right/Left External oblique; RIO/LIO = Right/Left Internal oblique). Measures with statistically significant differences between model calibration techniques are marked with an asterisk (*).

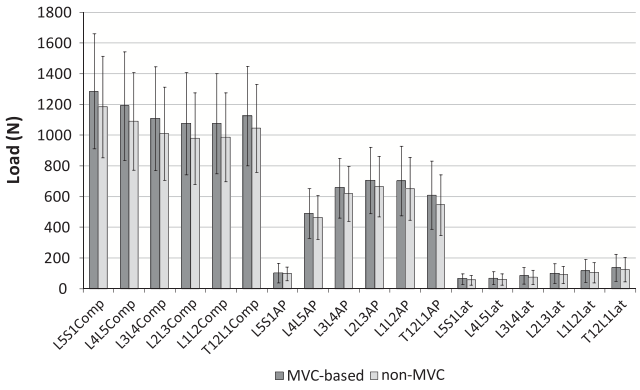

Fig. 3. Comparison of spinal loads between model calibration techniques for an independent test set of symmetrical and asymmetrical lifts (Comp = Compression; AP = Anterior–posterior shear; Lat = Lateral shear).

5. Discussion

The non-MVC model calibration technique evaluated in this study was found to meet all judgment criteria required for utilization. This technique was shown to have at least as low overall within subject gain ratio prediction variability, predict similar spinal loads, and result in equivalent model fidelity when compared to the established MVC-based technique. Additionally, the robustness of the non-MVC model calibration technique was demonstrated over a variety of complex free-dynamic exertions in multiple physiological planes simultaneously.

No statistically significant differences in spinal load predictions were found between model calibration techniques; however, spinal loads were consistently lower for non-MVC calibrations due to lower average gain ratio predictions in the extensor muscles (53.4 GRU vs. 63.9 GRU). Inflated MVC-based gain ratio and resultant spinal load predictions were expected since gain ratio and MVC are inversely related and MVCs were consistently underrepresented in this study. The non-MVC model calibration technique eliminates inherent error in gain ratio predictions due to sub-maximal MVCs and, thus, provides more reliable predictions of personalized muscle properties and resultant spinal loads.

Previous MVC-independent EMG normalization efforts have validated their techniques during controlled exertions where the pelvis was fixed and exertions were either performed only in the sagittal plane (Marras et al., 2001a) or in a static semi-seated posture (Cholewicki et al., 2011). The non-MVC model calibration technique presented in this study was validated across a range of free-dynamic (pelvis unconstrained) exertions in multiple physiological planes simultaneously and, thus, may be more applicable for evaluating realistic loading conditions. Additionally, the technique presented in this study does not require additional sub-maximal exertions for MVC prediction (Marras and Davis, 2001) and, thus, is less likely to fatigue subjects during calibration.

Twenty percent of the subjects evaluated in this study frequently produced myoelectric activities during experimental tasks that exceeded their MVCs. Similar behavior has been reported previously (Korkmaz et al., 2006; Splittstoesser et al., 2007). MVC-based calibrations for these subjects resulted in poor model fidelity. As a result, subsequent gain ratio and spinal load predictions could not be trusted, and data resulting from MVC-based calibrations for these subjects had to be removed. The non-MVC model calibration technique does not rely on MVCs and, thus, provides a means for evaluating spinal loads in subjects who are unwilling or unable to provide adequate MVCs.

In particular, patients who are symptomatic for LBP generally are unable to produce reliable MVCs due to associated pain (Keller et al., 1999). As a result, relatively little is known about spinal loading in LBP patients (Marras et al., 2001c, 2004). In order to explore the applicability of the non-MVC model calibration technique for LBP patients, two symptomatic LBP patients were evaluated as a supplement to this study. Patients were calibrated with the non-MVC technique and then asked to perform the same independent test set of symmetrical and asymmetrical lifts as the asymptomatic subjects who participated in this study. Patient gain ratio predictions fell well within the physiologically relevant range determined in this study (average of 33.9 GRU) and similar r^2 (.82) and AAE (14.9%) model fidelity measures were observed when compared to the asymptomatic population. These results indicate that the non-MVC model calibration technique appears to be a valid method for evaluating spinal loads in patients with LBP. Using the non-MVC model calibration technique as a tool for understanding spinal loading in LBP patients may provide significant insight into the underlying nature of the LBP disorder. Future studies are required to verify the performance of the non-MVC model calibration technique on a larger population of symptomatic LBP patients.

The calibration exertions and experimental tasks evaluated in this study were performed with relatively low to moderate loads since it was important to evaluate the non-MVC model calibration technique during conditions that could be performed by patients with low back pain. Typically, EMG-assisted models perform best at higher loading conditions and, thus, one would expect that the non-MVC technique would work at least as well as it did in this study when applied to conditions that require higher amounts of force. In order to examine this hypothesis, a single female subject was calibrated with both model calibration techniques and was asked to perform two sagittal lifts with 0, 7.71, and 16.8 kg loads. Average absolute errors observed during 0, 7.71, and 16.8 kg sagittal lifts, respectively were similar for models calibrated by the non-MVC (9.4%, 8.9%, and 8.3%) and MVC-based (10.3%, 9.8%, and 10.5%) calibration techniques. Similarly, r^2 values observed during 0, 7.71, and 16.9 kg sagittal lifts were .78, .85, .89 for models calibrated by the non-MVC technique and .78, .88, and .89 for models calibrated by the MVC-based technique. Both average absolute error and r^2 improved as load increased when the model was calibrated with the non-MVC technique, indicating that this technique would be applicable to higher levels of force generation. In general, low level exposures can be viewed as a worst case scenario for EMG-assisted biomechanical models since lower loads elicit lower muscle activations and, thus, create more potential for poor EMG signal to noise ratio. As a result, the model validity values reported in this study would likely be even better if heavier loading conditions had been used.

There are potential limitations to consider when interpreting experimental results from this study. Since muscle gain or gain ratio serve partially as an error factor, gain ratio limits defined here are valid only for the biologically-assisted model from which they were derived. Additionally, the gain ratio limits determined in this study were derived from MVC-based calibration data and, therefore, may be affected by underrepresented MVCs. However, since gain or gain ratio can compensate for scaling errors as long as physiological limits are not reached, these effects are expected to be minor. Finally, the same subjects who were used to compare calibration techniques in this study were also used to determine gain ratio limits. Since the gain ratio limits reported here envelop the mean observed gain ratio plus three standard deviations, however, these limits are expected to be valid for the general population.

6. Conclusions

This study has presented a biologically-assisted model calibration technique that does not require maximum voluntary contractions (MVCs) for EMG normalization. This technique was shown to have at least as low overall within subject gain ratio prediction variability, predict similar spinal loads, and result in equivalent model fidelity when compared to an established MVC-based technique. Additionally, the robustness of the presented model calibration technique was demonstrated over a variety of complex free-dynamic exertions in multiple physiological planes. It is now possible to predict reliable spinal loads for individuals who are unwilling or unable to produce adequate MVCs. In particular, this technique will allow researchers to explore spinal loading patterns in symptomatic LBP patients, which may provide significant insight into the underlying nature of the LBP disorder.

Conflict of interest

None declared.

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