Journal of Electromyography and Kinesiology 73 (2023) 102815

Contents lists available at ScienceDirect

Journal of Electromyography and Kinesiology

journal homepage: www.elsevier.com/locate/jelekin

The effect of back muscle fatigue on EMG and kinematics based estimation of low-back loads and active moments during manual lifting tasks

A. Tabasi [a,b,*], N.P. Brouwer [a], I. Kingma [a], W. van Dijk [b], M.P. de Looze [b], A. Moya-Esteban [c], H. v. d. Kooij [c], J.H. van Dieën [a]

[a] Dept. of Human Movement Sciences, Vrije Universiteit Amsterdam, Amsterdam, the Netherlands
[b] TNO, Leiden, the Netherlands
[c] Department of Biomechanical Engineering, University of Twente, Enschede, the Netherlands

ARTICLE INFO

Keywords:
Back muscle fatigue
Low-back load estimation
Exoskeleton control

ABSTRACT

This study investigated the effects of back muscle fatigue on the estimation of low-back loads and active low-back moments during lifting, using an EMG and kinematics based model calibrated with data from an unfatigued state. Fourteen participants performed lifting tasks in unfatigued and fatigued states. Fatigue was induced through semi-static forward bending. EMG, kinematics, and ground reaction forces were measured, and low-back loads were estimated using inverse dynamics and EMG-driven muscle model. A regression model was developed using data from a set of calibration lifts, and its accuracy was evaluated for unfatigued and fatigued lifts. During the fatigue-inducing task, the EMG amplitude increased by 2.8 %MVC, representing a 38% increase relative to the initial value. However, during the fatigued lifts, the peak EMG amplitude was found to be 1.6 %MVC higher than that observed during the unfatigued lifts, representing a mere 4% increase relative to the baseline unfatigued peak EMG amplitude. Kinematics and low-back load estimates remained unaffected. Regression model estimation errors remained unaffected for 5 kg lifts, but increased by no more than 5% of the peak active low-back moment for 15 kg lifts. We conclude that the regression-based estimation quality of active low-back moments can be maintained during periods of muscle fatigue, although errors may slightly increase for heavier loads.

1. Introduction

Physical loads exerted on the body have a significant impact on musculoskeletal health [Curtis et al., 2017; Kell et al., 2001]. Specifically, for the lower back, research has demonstrated that high mechanical loads contribute to an increased risk of low-back pain and injuries [Bergmann et al., 2017; Coenen et al., 2014]. Therefore, accurately quantifying the physical load on the lower back is crucial for identifying conditions that impose high mechanical demands on the body [Arjmand et al., 2011].

Due to the invasiveness of direct measurement of low back load, for instance through implantable load cells [Polga et al., 2004], low back load is commonly estimated utilizing biomechanical models [de Looze et al., 1992; Kingma et al., 1996; Patel and Ghasempoor, 2012; Schultz et al., 1983]. These models employ various measurable variables, including body kinematics, muscle activity, and external force sensors, to estimate low-back load.

It is important to note that these models are typically utilized in the absence of fatigue. However, research has demonstrated that fatigue can impact body kinematics and EMG signals of muscles [Enoka and Duchateau, 2008; Hu and Ning, 2015; Kazemi et al., 2022; Krogh-Lund and Jørgensen, 1991; van Dieën et al., 1993], which serve as inputs to the biomechanical models, and in turn can affect the performance of these models [Bonato et al., 2003]. Specifically, for those models that require adjustment of the model parameters for each individual, the alterations induced by fatigue can render the adjustments inaccurate or no longer valid, leading to inaccurate estimates of low-back load, which could especially be problematic when such estimates are used for applications such as providing feedback [Punt et al., 2020] or driving actuated exoskeletons [Fleischer and Hommel, 2006].

Few studies investigated the effects of fatigue on biomechanical model-based estimates of low-back loads by re-adapting the biomechanical model parameters in the fatigued state to accommodate the alterations induced by fatigue [Haddad and Mirka, 2013; Jia and Nussbaum, 2016; Sparto and Parnianpour, 1998]. The repeated adjustment of the muscle EMG-force relationship through frequent maximum

* Corresponding author.
E-mail address: ali.tabasi@vu.nl (A. Tabasi).

https://doi.org/10.1016/j.jelekin.2023.102815
Received 9 February 2023; Received in revised form 10 July 2023; Accepted 30 August 2023
Available online 3 September 2023

voluntary contraction (MVC) exertions has been demonstrated to aid in maintaining estimation quality [Sparto and Parnianpour, 1998]. Nevertheless, the practical challenges associated with this approach constrain the feasibility of using these models over extended durations and may contribute to accelerated fatigue development.

Haddad and Mirka [Haddad and Mirka, 2013] proposed a correction factor for the gain parameter, which represents the maximum muscle stress value per unit of cross-sectional area, to maintain accurate low-back load estimates with development of fatigue. The suggested correction factor is derived from the changes in Erector spinae EMG median frequency, which has been associated with the development of fatigue [Mannion and Dolan, 1994; van Dieën et al., 1993]. It should be acknowledged that the proposed correction factor was solely applied to the gain variable, while other influential factors, such as the muscle force–length relationship and muscle force–velocity relationship, may also be affected by fatigue [Gauthier et al., 1993; Jones, 2010]. Therefore, considering all the relevant parameters in the context of fatigue can offer a more accurate understanding of the impact of fatigue on the estimated low-back load.

Recently, we introduced a regression model [Tabasi et al., 2020] that estimates the moments generated by active back muscle forces. This model is based on an EMG-driven musculoskeletal model [van Dieën and Kingma, 2005] which calculates trunk muscle and passive tissue forces using low-back kinematics and 12 trunk muscle EMG signals. The regression model, however, uses only two EMG channels and measurements of trunk inclination and lumbar flexion as inputs, to accurately predict ($R^2 > 0.92$) the active low-back moment. While the reduced input requirements of the regression model enhances its practical feasibility, adjusting the EMG-driven model parameters and fitting the regression model for each individual are essential calibration steps [Tabasi et al., 2022].

Typically, the regression model is calibrated in an unfatigued state. However, with the development of fatigue, the estimation errors may increase. Therefore, this study investigated the impact of back muscle fatigue on body kinematics, back muscle EMGs and calibration-based active low-back moment estimation errors during lifting. If fatigue effects are minor, this shows that estimation quality can be maintained and, this enhances the feasibility of implementing the calibration-based methods over extended durations.

2. Methods

2.1. Participants

Fourteen male participants (26.9 ± 5.4 years; 1.79 ± 0.09 m; 74.9 ± 11.7 kg) without low-back pain participated in this study. They signed informed consent after being informed of the experimental protocol which was approved by the University of Twente Ethics committee (ref. 2020.15).

2.2. Experimental procedure

The experimental protocol consisted of four parts: (1) preparation, (2) lifts in unfatigued state, (3) a task to induce back muscle fatigue, and (4) lifts in fatigued state. In the first part, motion capture markers and EMG sensors were attached to measure body kinematics and muscle activity, followed by motion capture sensor calibration and maximum exertion tasks to obtain maximal voluntary contractions (MVC). In the second part, participants lifted and lowered a box (height 22 cm, depth 30 cm, width 40 cm) from the floor to an upright standing posture (Fig. 1a) using stoop (extended knees and reaching the box with trunk flexion), squat (extended trunk and reaching the box with knee flexion) and free (a self-selected combination of knee and trunk flexion) techniques with 5 and 15 kg loads in randomized order, while each trial included four repetitions. In the third part, participants performed semi-static forward bending (Fig. 1b) while receiving auditory and visual feedback to maintain a bending angle of 30 ± 3 degrees. This angle was measured using an inertial measurement unit (Xsens, Enschede, The Netherlands) attached at the T10 spinous process height, and the feedback was provided through a custom-made script (MATLAB, MathWorks, Natick, US). To ensure that the bend was achieved through lumbar flexion alone and not hip rotation, participants wore a structure that constrained their hip joints in their anatomical neutral orientation. They were instructed to keep their arms relaxed and their knees straight. The task continued until the participant indicated that he could not maintain the posture, thus ensuring back muscle fatigue. The structure was then promptly removed to minimize any recovery from fatigue and the participants moved on to the fourth part. The fourth part included the same lifts as the second part but with the back muscles in a fatigued state.

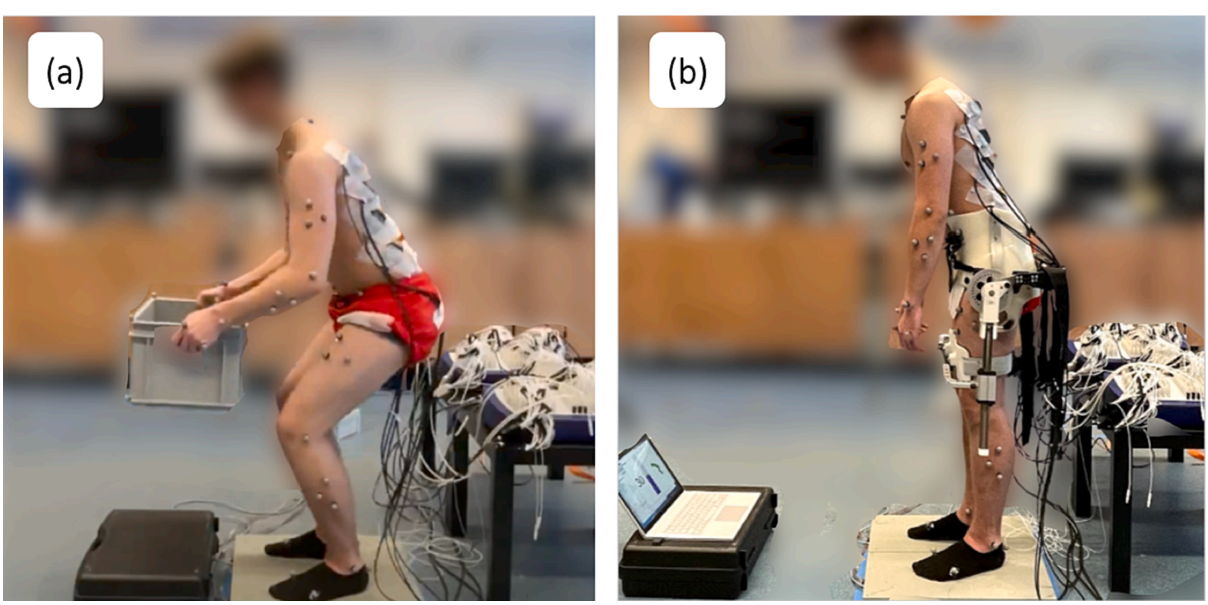

Fig. 1. Experimental procedure. (a) Participants lifting a box under various conditions, including different lifting techniques and weights. Free technique lifting is depicted as an example. (b) Participants performed semi-static forward bending until exhaustion with auditory and visual feedback to maintain 30 ± 3 degrees bending angle, while wearing a structure constraining the hip joints in the anatomical neutral position.

2.3. Data acquisition

2.3.1. Trunk muscle EMG

During the preparation, eight 8 × 8 electrode grids (AgCl, inter-electrode distance 8.5 mm, distance between outer electrodes of each grid and the grid edge 4.25 mm) were attached to the shaved and cleaned skin on the back (Fig. 2a).

The grids were placed bilaterally 1 cm from the spine (four per side), stacked with a 1 cm inter-grid distance, starting at the height of the L5 spinous process towards the upper back. Full grid data were used for analysis of the fatigue-inducing task, published elsewhere [Brouwer et al., 2022]. In the current study, back muscle EMG signals were obtained using bipolar configurations created from electrodes placed at locations consistent with previous research, i.e., Iliocostalis lumborum 6 cm lateral to L2, longissimus thoracis pars lumborum 3 cm lateral to L1, longissimus thoracis pars thoracis 4 cm lateral to T9 [van Dieën and Kingma, 2005]. The signals were obtained by averaging 5 electrodes, simulating the monopolar signals of a larger electrode, and subtracting signals of adjacent groups to calculated the bipolar signal. When the central electrode was at the edge of the grid, 4 electrodes were used (Fig. 2a). In addition, three pairs of electrodes were attached to the skin region above the right Rectus Abdominus (over the muscle at the umbilicus level), Internal (just superior to the inguinal ligament) and External (15 cm cranial of the anterior superior iliac spine) Oblique to capture abdominal muscle activities (Fig. 2b). EMG signals were recorded at 2048 Hz using REFA (TMSi, Oldenzaal, The Netherlands) and synchronized with marker position and ground reaction forces using the Qualisys Track Manager. These signals were band-pass filtered (10–400 Hz) with a second-order Butterworth filter, band-stop filtered to remove the electrical noise [Mewett et al., 2001], high-pass filtered (30 Hz) to remove ECG artifacts [Redfern et al., 1993], full-wave rectified and low-pass filtered (2.5 Hz) to determine the linear envelope [Potvin, 1996].

To verify muscle fatigue, repeated measures ANOVA compared the normalized amplitude and the median frequency of the EMG signals during the first and last minute of the fatigue-inducing task [Phinyomark et al., 2012]. Time (first minute, last minute) and muscle group were considered as factors. Additionally, the peak normalized EMG amplitudes during unfatigued and fatigued lifts were compared.

2.3.2. Kinematics and ground reaction forces

A Qualisys motion capture system (Qualisys, Gothenburg, Sweden) was used to obtain kinematics, using reflective markers attached to anatomical bony landmarks (Fig. 2c) and ten cameras capturing these markers at 128 Hz, with ground reaction forces and moments measured by AMTI dual force plate (AMTI, MA, USA).

2.4. Low-back compression force and moments

The EMG-Model employs musculoskeletal anatomy, encompassing the spatial arrangement and configuration of bones, joints, and muscles, along with the EMG-force relationships, including force–length, force–velocity, and passive force generation, to establish the interrelationship between the linear envelopes of the EMG signals and the lumbar flexion angle on one hand, and the generation of active and passive moments by the muscles and other trunk tissues on the other hand. This model includes six parameters that represent subject-specific muscle contractile properties [van Dieën and Kingma, 2005], which are, based on measured net moments during the calibration lifts, optimized to minimize the difference between the net moment pattern, and the moment generated by the muscle model. These parameters consist of: (1) gain factor for the EMG-force relationship, (2) scaling factor for the width of the active force–length curve representing muscle active force–length relationship, (3, 4) scaling factors for the active force–velocity relationships encompassing both eccentric and concentric contractions, and (5,6) scaling factor and offset factor for the passive length–force curve representing passive force generation by muscles and other trunk tissues [van Dieën and Kingma, 2005]. The EMG-Model utilizes these parameters to refine the aforementioned relationships for each subject specifically, allowing for the estimation of the active and passive forces generated by the back muscles and other trunk tissues based on the analysis of EMG signals and the lumbar flexion angle.

These parameters are determined by minimizing the difference between the inverse-dynamics-based net moment around the L5S1 joint and the moment due to active and passive counterbalancing forces. Optimal EMG-Model parameters may vary between unfatigued and fatigued states of the back muscles, due to fatigue induced changes in contractile properties. Thus, separate determination is necessary for best estimates, but may not be feasible in practical applications. To address this, active low-back moments were also calculated for both muscle states using the calibration-based approach with unfatigued state data for calibration, to investigate the effects of fatigue on the estimation accuracy of this method. The best estimate and calibration-based

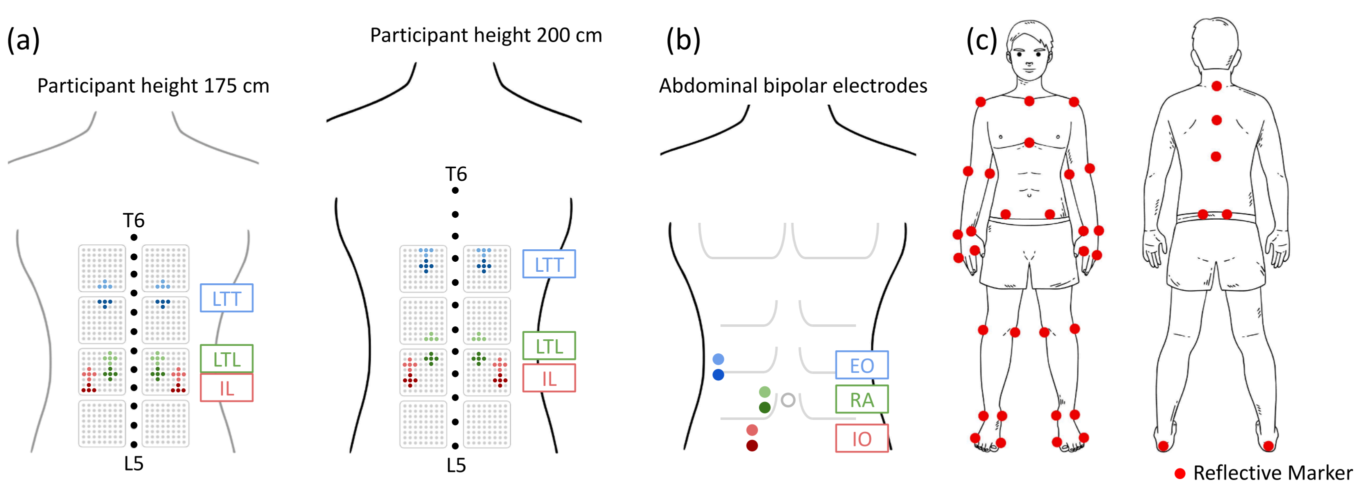

Fig. 2. Sensor placement diagram. (a) Examples of electrode grids placement on the back for two participants. EMG signals were obtained using the electrode groups located above Iliocostalis lumborum (red), Longissimus thoracis pars lumborum (green), Longissimus thoracis pars thoracis (blue). Light and dark shades represent two adjacent groups of electrodes that were used to construct a bipolar configuration. (b) Example of electrode placement on the abdominal muscles. EMG signals were obtained using electrode pairs located above Rectus abdominus (green), Internal oblique (red) and External oblique (blue). Light and dark shades represent two electrodes that were used to construct a bipolar configuration. (c) Reflective markers attached to anatomical bony landmarks. (For interpretation of the references to colour in this figure legend, the reader is referred to the web version of this article.)

approaches will be explained in the following sections.

2.5. Best estimate

The best estimates of the low-back compression force and active moment during lifts were obtained by, first using inverse dynamics to determine the net moment around the L5/S1, taking into account the body segments and box kinematics, and ground reaction forces [Kingma et al., 1996]. Second, the EMG-Model parameters were determined using the EMG signals, lumbar flexion angle, and the net moment [van Dieën and Kingma, 2005]. Two sets of EMG-Model parameters were calculated: one for the unfatigued lifts and another for the fatigued lifts to account for potential changes due to fatigue. Third, the low-back compression force and active moment were calculated using the EMG signals, lumbar flexion angle, and the associated parameters, considered the best estimates.

2.6. Calibration-based estimates

The model for calibration-based estimates was calibrated using data from unfatigued lifts. The process involved fitting a third-degree polynomial regression model between two EMG amplitudes (bilateral longissimus thoracis pars thoracis), trunk inclination angle and lumbar flexion angle as independent variables, and the best estimate of the active low-back moment as the dependent variable [Tabasi et al., 2020], using a custom-made script (MATLAB, MathWorks, Natick, US). The data subset used for calibration was the first and second repetitions of unfatigued lifts.

The calibration-based model was then employed to estimate the active low-back moments during the third and fourth repetitions of the unfatigued lifts and the first and second repetitions of the fatigued lifts. These estimates are referred to as calibration-based estimates. Data from the third and fourth repetitions of the unfatigued lifts were used to prevent using the same dataset for training and testing the regression model. Data from the first and second repetitions of the fatigued lifts were used to prevent underestimating fatigue effects due to potential muscle recovery.

2.7. Evaluation and statistics

Peak back muscle activity, peak rotation angles (lumbar flexion angle, trunk inclination, hip and knee joint), peak net moment around the L5/S1 and the best estimate of peak low-back compression force and active moment were determined during each unfatigued lift, averaged among the participants and compared with those of the fatigued lifts. The peak values were chosen for comparison as they describe the range of motion for joints and indicate excessive forces and moments that may cause injury. Moreover, the peak values of calibration-based estimates of the active low-back moment were compared with those obtained with the best estimate approach for unfatigued and fatigued lifts separately (Fig. 3). This comparison allows evaluation of the regression model performance for unfatigued lifts and any additional changes in the estimation accuracy caused by muscle fatigue for fatigued lifts.

The effect of fatigue on the regression model was investigated by comparing estimation errors (calibration-based versus best estimate). The difference and the absolute value of the difference of the peak active moment estimation errors between unfatigued and fatigued states were used as dependent variables.

Repeated measures ANOVA was performed on the above-mentioned evaluation parameters, followed by post-hoc Bonferroni tests. Factors considered in the analysis were muscle state (unfatigued, fatigued), box mass (5, 15 kg) and lifting technique (stoop, squat, free). Additionally, joint, muscle group, and estimation method (best estimate, calibration-based) were considered for peak rotation angles, muscle activity, and active low-back moments, respectively. The main effects of muscle state and estimation method and their interactions with box mass and lifting technique were investigated. The main effects of box mass, lifting technique, joint and muscle group and their interactions were considered in the statistical model, but not reported as they were not relevant to this study. A significance level of 0.05 was considered.

3. Results

3.1. Back muscle EMG

Averaged among participants and across all back muscles, the normalized EMG amplitudes increased (Fig. 4, $p < 0.001$) by 2.8(0.6) %

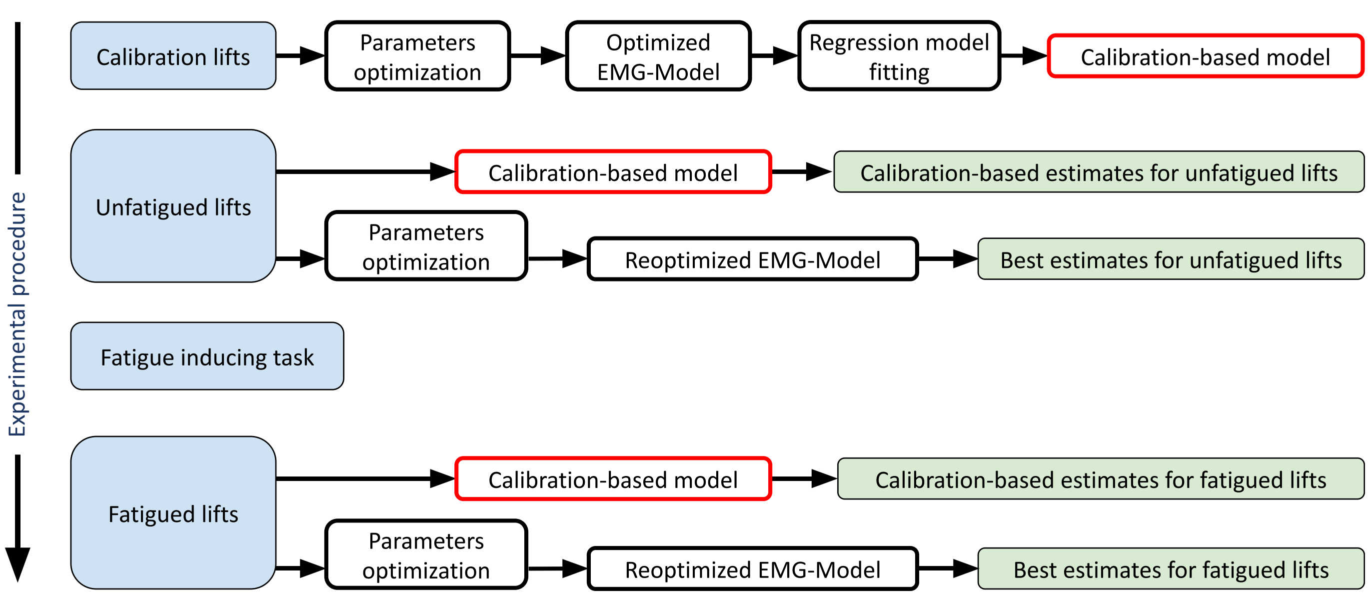

Fig. 3. Evaluation pipeline: Creating the calibration-based model using calibration data, estimating active low-back moments using the calibration-based model and re-optimizing the EMG-Model to determine best estimates for unfatigued and fatigued lifts.

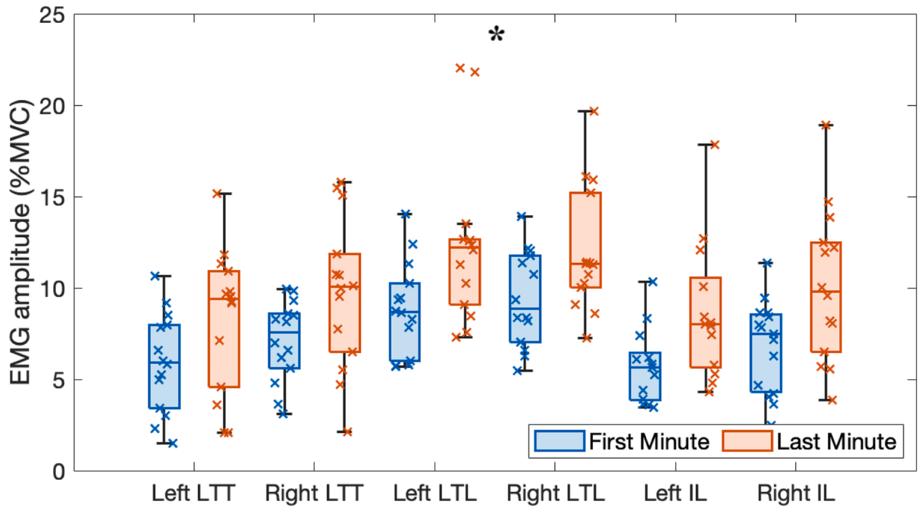

Fig. 4. Linear envelope of normalized EMG signals of longissimus thoracis pars thoracis (LTT), longissimus thoracis pars lumborum (LTL) and Iliocostalis lumborum (IL) increased when comparing the last minute of the fatigue-inducing task to the first minute. Each cross (×) represents the linear envelope for a single participant. Asterisk (*) indicates a significant main effect of fatigue (over all muscles).

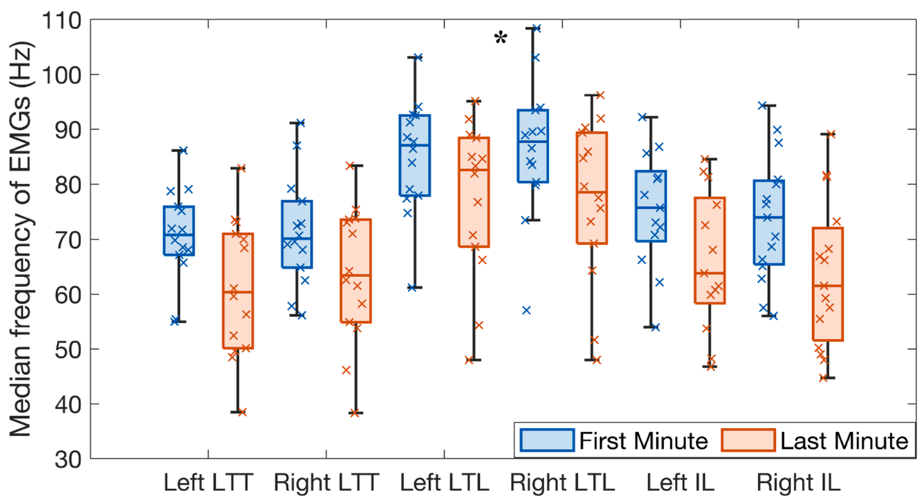

Fig. 5. Median frequency of EMG signals of longissimus thoracis pars thoracis (LTT), longissimus thoracis pars lumborum (LTL) and Iliocostalis lumborum (IL) decreased when comparing the last minute of the fatigue-inducing task to the first minute. Each cross (×) represents the median frequency for a single participant. Asterisk (*) indicates a significant main effect of fatigue (over all muscles).

MVC (Mean(Std. Error)), representing a 38% increase relative to the initial value, and median frequencies decreased (Fig. 5, $p = 0.011$) by 9.0(3.0) Hz between the first and the last minute of the fatigue-inducing task.

Averaged among participants and across all back muscles, the Peak EMG amplitudes were 34.9(18.6) %MVC during unfatigued lifts and 36.5(19.0) %MVC for the fatigued lifts ($p = 0.018$, Fig. 6), indicating a 4% increase relative to the baseline unfatigued peak EMG amplitude in the presence of muscle fatigue.

3.2. Kinematics

The peak lumbar flexion angle, trunk inclination angle, hip flexion angle, and knee flexion angle during lifting (Table 1) were not affected by fatigue ($p = 0.986$) and there was no significant interaction effect between muscle state and joint ($p = 0.659$).

3.3. Low-back compression force and moments

Muscle fatigue did not affect the peak net moment around the L5/S1 ($p = 0.667$), the best estimate of peak low-back compression force ($p = 0.485$), nor the best estimate of peak active low-back moment ($p = 0.167$). Additionally, there was no main effect of the estimation method on the peak active low-back moment for both the unfatigued ($p = 0.845$) and fatigued lifts ($p = 0.467$). No interaction effects were found between the estimation method and the load (unfatigued lifts $p = 0.754$, fatigued lifts $p = 0.281$) and between the estimation method and the lifting technique (unfatigued lifts $p = 0.251$, fatigued lifts $p = 0.367$) (Table 1).

A follow-up test compared the estimation errors (i.e., best estimate minus calibration-based) between unfatigued and fatigued states and found no significant main effects of fatigue on the estimation error ($p = 0.227$), nor on the absolute estimation error ($p = 0.062$). However, there was an interaction effect of muscle state and load on the absolute estimation error ($p = 0.031$, Fig. 7). Further analysis revealed that there was no effect of fatigue on the absolute estimation error (unfatigued 7(1)

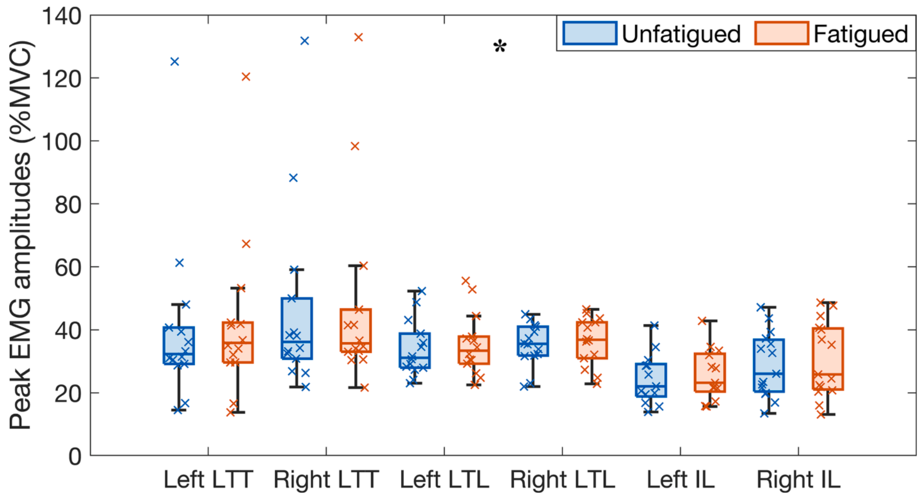

Fig. 6. Peak normalized EMG amplitude of longissimus thoracis pars thoracis (LTT), longissimus thoracis pars lumborum (LTL) and Iliocostalis lumborum (IL) were slightly higher during fatigued lifts compared to unfatigued lifts. Each cross (×) represents the peak value for a single participant. Asterisk (*) indicates a significant main effect of fatigue (over all muscles).

Table 1
Peak values (Mean (Std. Error)) during lifts in unfatigued and fatigued muscle state.

	Unfatigued	Fatigued
Lumbar flexion (degrees)	23.8 (2.5)	23.1 (2.5)
Trunk inclination (degrees)	59.4 (2.5)	59.2 (2.0)
Hip rotation (degrees)	76.9 (2.9)	76.9 (2.9)
Knee rotation (degrees)	88.0 (2.1)	89.0 (2.5)
Net moment (Nm)	157 (5)	156 (6)
Compression force (N)	3825 (126)	3844 (129)
Active moment (Best estimate) (Nm)	129 (7)	132 (7)
Active moment (Calibration-based) (Nm)	127 (6)	135 (6)
Estimation error (Nm)	1 (3)	−3 (4)
Absolute estimation error (Nm)	8 (1)	13 (3)

Nm), fatigued 9(2) Nm, $p = 0.353$) for 5 kg lifts, but there were higher absolute estimation errors for lifts with a 15 kg load in the fatigued state (17(4) Nm) compared to the unfatigued state (10(2) Nm) (Fig. 7).

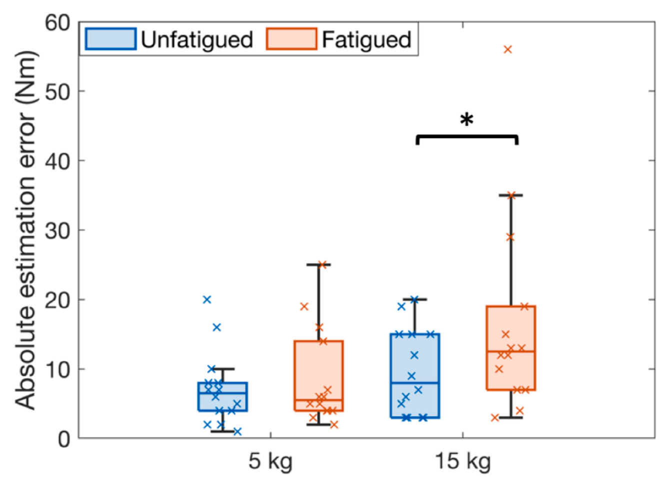

Fig. 7. Absolute estimation errors for unfatigued and fatigued lifts. Errors were higher with 15 kg lifts, but not affected by fatigue with 5 kg lifts. Each cross (×) represents the error for a single participant. The asterisk (*) denotes a significant difference ($p < 0.05$).

4. Discussion

In this study, we investigated the effects of low-back muscle fatigue on back muscle EMGs, body kinematics, estimates of low-back loads, and active low-back moments during lifting. During the fatigue-inducing task, EMG amplitudes showed an increase, starting from an average of 7.3(2.8) %MVC in the first minute and reaching 10.2(4.2) %MVC in the last minute, reflecting a 38% increase relative to the initial value. However, in the subsequent lifts, there was an average increase of 1.6 (0.6) %MVC in the Peak normalized EMG amplitude relative to unfatigued lifts, amounting to only a 4% increase relative to the value observed during the unfatigued lifts. Kinematics and low-back loads remained unaffected. Active low-back moment estimation errors for lifts with a 5 kg load were unchanged but increased when fatigued for lifts with a 15 kg load.

4.1. Back muscle EMG

The fatigue-inducing task was continued until exhaustion and thus, the development of back muscle fatigue was anticipated. The increase in amplitude and the decrease in the median frequency of EMG signals are reliable indicators of muscle fatigue [Enoka and Duchateau, 2008; van Dieën et al., 1993]. The decrease in the median frequency was 7% and 15% relative to the initial value for longissimus thoracis pars lumborum and Iliocostalis lumborum, respectively, similar to the 15% reduction reported by [van Dieën et al., 1993] for isometric contractions until exhaustion.

The peak EMG amplitudes during the fatigued lifts were 1.6(0.6) % MVC higher than those observed in the unfatigued lifts, indicating only a 4% increase relative to the value observed during the unfatigued lifts. This was lower than the increase during the fatigue-inducing trial (7.3 (2.8) to 10.2(4.2) %MVC, representing a 38% increase relative to the initial value, Part 3). Previous studies have indicated that the manifestation of fatigue in EMG amplitude recovers quickly [Bonato et al., 2003], likely due to the recovery of central fatigue [Krogh-Lund, 1993]. Peripheral fatigue, however, which is mainly caused by lactate accumulation, is expected to last longer but may have a reduced manifestation in EMG amplitude [Krogh-Lund, 1993]. The high levels of subjective fatigue reported by all participants during the fatigued lifts, based on their informal self-assessments, provide additional evidence of the presence of muscle fatigue during these lifts. So, despite rapid recovery of EMG we are confident that there was still substantial local muscle fatigue during Part 4. Clearly, we cannot exclude that some further recovery occurred during lifts in fatigued state. However, the fatigue task during Part 3 was relatively low intensity, and it took a substantial amount of time to reach exhaustion (24.5(11) minutes), which was chosen because slowly developed fatigue also results in slow recovery [Kuorinka, 1988]. Moreover, fatigued lifts were started quickly after the static fatigue trial, and pauses between trials were minimized. While the randomization of trial order over participants hampers direct interpretation of changes in EMG over time during the lifts, when averaging data over participants and plotting peak EMG against trial order, we could not detect substantial changes in differences between unfatigued and fatigued trials over time as shown in Figure S1 in the supplementary material.

4.2. Kinematics

The kinematic measures during lifting, i.e., peak lumbar flexion angle, trunk inclination angle, hip rotation angle, and knee rotation angle, were not affected by back muscle fatigue. The unchanged peak lumbar flexion angle suggests that the participants did not shift to relying more on passive forces after fatigue, which is in contrast to the findings of a previous study [Sparto et al., 1997] that reported an increase in reliance on passive tissues as a result of fatigue caused by a repetitive lifting task. In the current study, a prolonged semi-static forward bending task was chosen to ensure that back muscle fatigue caused the exhaustion as (semi-)static contractions are known to induce larger changes in EMG than dynamic contractions [Hagberg, 1981]. A repetitive lifting task however, affects multiple muscle groups and may, for example, lead to reduced knee flexion compensated by increased trunk flexion over time.

4.3. Low-back compression force and moments

The results indicated that the peak net moment around the L5/S1 was not affected by fatigue. This is because the peak net moment is determined by the body segment masses, external load, and joint kinematics. Since the mass of the body segments and external loads were similar for both unfatigued and fatigued lifts, the unchanged peak net moment can be attributed to the unaffected kinematics during the fatigued lifts.

In addition, the best estimates of peak low-back compression force and peak active low-back moment were unaffected by fatigue. This suggests that the balance of active and passive low-back force contributions, and the resulting compression force, remained the same even with an increase in EMG amplitude due to fatigue. The consistent passive contribution was a consequence of the unaffected lumbar flexion angle. The unchanged forces, despite the increase in EMG amplitudes, can be explained by the changes in the EMG-force relationship caused by fatigue [Sparto and Parnianpour, 1998]. The EMG-force relationship was adjusted in the EMG-Model during the optimization process and the changes were considered by reoptimizing the model parameters in the best estimate approach after fatigue.

The quality of the calibration-based estimation of peak active low-back moments was examined in three ways. The first test compared the peak active low-back moment estimated by the calibration-based approach with those determined by the best estimate approach. It was found that there was no effect of the estimation method on unfatigued lifts, as previously reported [Tabasi et al., 2020], and this held for fatigued lifts as well.

The second test compared the estimation errors (best estimate minus calibration-based) between the unfatigued and fatigued lifts and found no effect of fatigue on the estimation error. The results of the first and second tests suggest that the calibration-based method does not exhibit any bias towards overestimating or underestimating peak active low-back moments, which remained consistent even after inducing fatigue.

The third test compared the absolute estimation errors between the unfatigued and fatigued lifts and revealed larger error magnitudes during 15 kg fatigued lifts only. This can be attributed to the fact that the regression model uses kinematics and EMG signals to estimate the low-back load, which is composed of (1) loads due to the body mass and (2) loads due to the object lifted. When accounting for the load from body mass, the model likely relies more on kinematics, which did not change with fatigue. However, when accounting for the load from the object lifted, the model relies more on EMG signals. Therefore, lifting a heavier object increases the impact of EMGs on the model's estimates. This heightened impact of EMG, along with the changes in EMG signals caused by fatigue, likely contributed to the higher estimation errors observed during 15 kg fatigued lifts.

4.4. Limitations

We found minor effects of fatigue on estimation performance. However, this study is subject to several limitations. The first limitation is that other forms of fatigue induction, e.g., by repetitive lifting, may have a greater impact on kinematics or EMGs. To specifically evaluate back muscle fatigue effects, we used a prolonged semi-static forward bending task to induce fatigue, expecting substantial back muscle fatigue and changes in EMG.

The second limitation is that some participants had relatively high estimation errors (Fig. 7). The estimation accuracy depends on the performance of the EMG-Model and of the regression model. Poor performance of either model may lead to relatively large estimation errors, which is troublesome for exoskeleton control. These errors might be caused by anatomical sources of error, location of the EMG electrodes, and excess body fat [Chowdhury et al., 2013; van Dieën and Kingma, 2005]. Poor estimation quality can be detected through relatively large errors during calibration, i.e., large errors of the EMG-Model optimization or poor fit of the regression model. For instance, the maximum values of the absolute error in all four subgroups in Fig. 7 belong to one participant with a root-mean-square error of 11 Nm in fitting the regression model, while the root-mean-square error for the other participants was 6(0) Nm. Finally, static postures were maintained until exhaustion, but this may not have resulted in the same level of muscle fatigue across participants [Mannion et al., 2011].

5. Conclusion

In conclusion, the results of this study demonstrate that low-back muscle fatigue has a limited effect on lifting biomechanics and the quality of active moment estimation. While back muscle fatigue resulted in an increase in EMG amplitude and a decrease in median frequency during a fatigue-inducing task, peak EMG amplitudes during the fatigued lifts were only slightly higher than those of the unfatigued lifts. Kinematic measures and low-back loads were not affected by fatigue. The estimation quality of a regression-based biomechanical model for estimating active low-back moments was not affected by fatigue for lifts with a 5 kg load, but was slightly decreased for lifts with a 15 kg load. These findings suggest that a model calibrated in an unfatigued state can accurately estimate active low-back moments during lifting tasks, also in the presence of muscle fatigue, making it viable for prolonged exoskeleton use. However, caution should be taken when applying such methods for lifting heavy loads in a fatigued state.

Declaration of Competing Interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

Acknowledgment

This research was funded by TNO's i-Botics Research Program and the Dutch Research Council (NWO, project P16-05) as part of the Wearable Robotics research program.

During the preparation of this work the author(s) used [ChatGPT / OpenAI] in order to improve language and readability. After using this

tool/service, the author(s) reviewed and edited the content as needed and take(s) full responsibility for the content of the publication.

Appendix A. Supplementary material

Supplementary data to this article can be found online at https://doi.org/10.1016/j.jelekin.2023.102815.

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