Deep-Learning Based Lumbar Moment Estimation during Exosuit Augmented Lifting with Variable Loading Conditions

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Abstract—**Wearable robotic devices have shown promise in aiding the mitigation of lower back injuries by reducing strain on muscles within the posterior chain, predominantly the erector spinae. Being a determinant of muscle strain, lumbar moments represent valuable measurements in assessing the efficacy of such devices and could further provide a more granular control input than kinematically derived heuristics. To date, computing lumbar moments is a cumbersome process, largely due to the time-intensive setup and processing requirements associated with optical motion capture (OMC) based inverse dynamics. Despite recent advances in wearable sensor-based alternatives, these limitations complicate studies that investigate real-time assistance adaptations to variations in task or loading conditions, which could ultimately provide valuable insight into how differences in control strategies affect spine kinetics and injury risk. Here, we explore the potential of using body-worn, inertial measurement units in combination with lab-integrated force plates, instead of a fully OMC based approach to estimate lumbar moments within participants. To this end, we examine two deep learning architectures, a baseline fully connected neural network (FCNN) and a long-short-term memory (LSTM) network, particularly suited for capturing temporal dependencies within the input data. We validated our approach on experiment conditions and external loads that were not present within the training set. Both models achieved high accuracy (1.58 ± 1.02 Nm RMSE) and excellent correlation (r = 0.95 ± 0.06) with OMC-based lumbar moment estimates.**

I. INTRODUCTION

As an emerging assistive technology, wearable robotic devices such as back exosuits and exoskeletons have been proposed to mitigate the risk of back injury in occupational settings and augment rehabilitation after the onset of low back pain (LBP) [1], [2], [3]. Most devices in this context deploy either passive or active actuation strategies [4]. Passive systems rely on spring-loaded assistance mechanisms that provide support by storing and releasing energy throughout the flexion-extension cycle. For active systems, assistance is generated from electric motors and can be controlled by mapping sensor information for example from device integrated inertial measurement units (IMUs) to desired force outputs. While the etiology of back injuries is often multifactorial, instances of high peak or cumulative loading frequently contribute to back overexertion, making a reduction in lumbar moment (LM) and, thereby, tissue strain a primary objective of exosuit augmentation [5].

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Back devices often deliver assistance proportional to sagittal plane trunk kinematics, a heuristic guided by the increasing horizontal distance of the body's center of mass around the lumbar joint with increasing trunk flexion [3], [4]. However, this form of assistance scaling remains naive to changes in lumbar moments specific to individuals and tasks. That is, the exact torso (center of) mass is typically unknown and varies between individuals. Moreover, variations in loading state may impact the amount of stabilizing moment the back extensor muscles have to generate [6], without necessarily influencing overall trunk kinematics. Under such circumstances, the biomechanical effectiveness (i.e., its moment reduction relative to task demand) of an assistive device could diminish [6]. Estimating back extensor moments directly on the other hand may guide development of task and payload sensitive assistance profiles [7], offering the potential to improve upon the exosuits biomechanical and perceptual effectiveness. Currently, the reference standard for computing LMs is laboratory-based inverse dynamics, a laborious process that involves placing reflective markers on anatomical landmarks to build a detailed, user-specific kinematic model, using optical motion capture (OMC) technology. Combining this model with kinetic information (e.g., from floor-integrated force plates) and estimates of body anthropometrics allows to eventually compute moments along the kinematic chain.

Given the constraints imposed by an OMC based inverse dynamics pipeline, measuring lumbar moments non-invasively in near real-time is challenging. While highly accurate kinetic information requires access to lab-integrated force plates, such data could be read and processed in real-time or replaced entirely with data from more accessible technology such as mobile pressure mats or insoles [8]. Constructing and analyzing a kinematic model however remains a complex and time-consuming task, mainly due to the need for correcting marker trajectories in post-processing and adjusting models accordingly. Considerable work has explored wearable alternative solutions using motion sensors such as IMUs, often complemented by pressure insoles or loading state as sources of kinetic information, to predict lumbar moments in the field [8], [9]. To this end, existing studies have predominantly investigated approaches constructing explicit IMU or electromyography-informed [10] inverse kinematic models [11], while end-to-end/machine learning (ML) methods have started to be explored more extensively over the last years [8]. Kinematic models rely upon user-specific sensor-to-joint calibrations (before each use) to adapt to individual anatomical

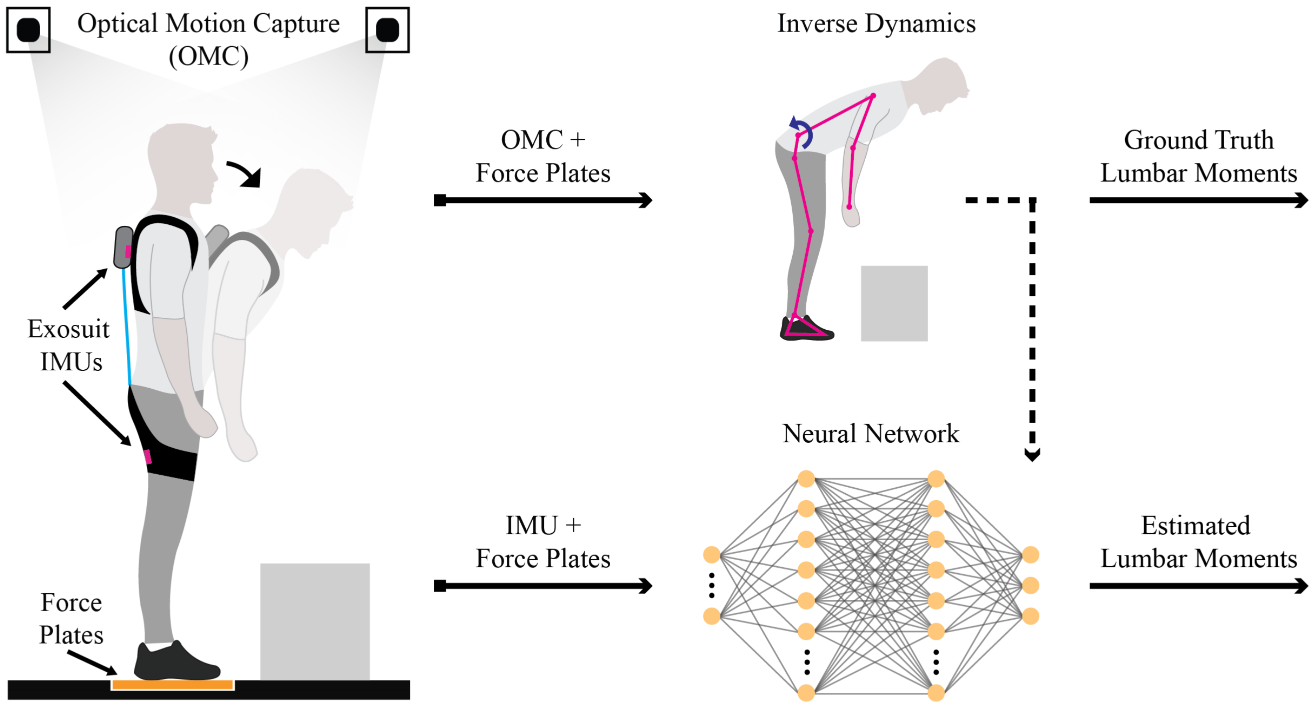

Figure 1. Experimental Setup. Participants wore a soft exosuit with IMUs integrated on the upper body and on both posterior thigh components. Standing on lab integrated force plates, individuals went through a series of lifting tasks, involving varying external loads. From these tasks we computed true lumbar moments with inverse dynamics, using optical motion capture technology. Those lumbar moments represented the target variables for two neural networks that were trained to estimate these lumbar moments based on input features from IMUs and force plates.

differences. Moreover, the required number of sensors scales with increasing model complexity/degrees of freedom. Removal of sensors requires changes in model assumptions [12]. Meanwhile, purely data driven models seek to learn the underlying relationship between sensor data and lumbar moments implicitly which, with sufficient training, may reduce user-specific adaptation requirements. Estimating lumbar moments under variable loading conditions without onerous calibration would be ideal for identifying movements that could be precursors to injury. While such ML based approaches have shown promise in generalizing predictions across individuals [8], estimation errors to date may not yet be sufficiently low to rely upon estimated moments as control inputs. On the other hand, models trained and capable of generalizing to new tasks or loads within a subject have only recently been explored [10]. Meanwhile, such approaches may offer the potential to reduce reliance on OMC technology by increasing the ability to accurately predict lumbar moments, while imposing reasonable training/calibration effort (e.g., requiring a single OMC-based visit).

Here, we explore the potential of using body-worn, inertial measurement units in combination with lab-integrated force plates to estimate within-participant lumbar moments. To this end, we compare two deep learning approaches, a fully connected neural network (FCNN) capable of learning direct, non-linear mappings from sensor signals to joint moments as well as a long-short-term-memory (LSTM) to investigate if accounting for temporal relationships within the input data can offer improvements in prediction accuracy. Both models were trained based on ground truth OMC-based lumbar moments (see Fig. 1) and validated on data from a previously excluded trial, which only comprised external loads that were not part of the training set (see Fig. 2). We demonstrate that after having undergone an initial training/calibration visit, we can accurately estimate lumbar moments under unfamiliar experiment conditions, relying only on three IMUs and bilateral force plate data.

II. METHODS

A. *Participants*

Fourteen participants (seven female, height 170 ± 10 cm, weight 69.3 ± 13.3 kg) volunteered for this study. All participants were screened to be healthy, with no recent back injuries, performing physical activity at least three hours a week. Consenting to a study protocol approved by Harvard Medical School's Internal Review Board (IRB 20-1667).

B. *Protocol*

Participants first underwent a familiarization session with the exosuit to ensure they could complete all experimental tasks. They were prepared for motion capture, placing reflective markers on 22 bony landmarks to construct segment models of the foot, shank, thigh, pelvis, and torso [13]. Participants placed their right and left foot on separate force plates (Bertec) and assumed a T-pose for calibration. Marker and force plate data were recorded using 31 infrared emitting cameras (Oqus700 and Arqus A9, Qualisys) at 200 Hz using the Qualisys Track Manager (QTM, Version 2020.2, Qualisys^{TM}, Goteborg, Sweden).

A researcher assisted the participant with comfortably donning a back exosuit designed to actively deliver assistance

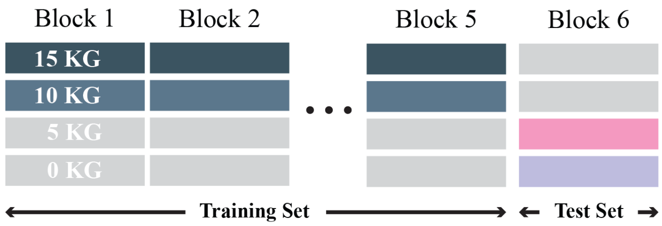

Figure 2. Training and test set structure. One block (i.e., condition) was held out as the test set. For the remaining blocks, only external loads 10 kg and 15 kg (if available) were considered for training (dark blue). Predictions were generated only on the loads 0 kg (purple) and 5 kg (pink) from the test set.

using a controller informed by three inertial measurement units (IMUs, BN0085, BOSCH SensorTec GmbH, Reutlingen, Germany) located posteriorly on the left and right thigh and near the actuator in the exosuits back panel [14]. IMU data were synchronized with QTM and sampled at 100 Hz using an eight-bit micro processing unit (PIC18F25K80, Microchip Technology, Inc., AZ, USA) and an onboard flash memory card (SDSQUNC-032G-AN6IA, Scandisk, CA, USA). Between each block, data was retrieved from the flash card by power cycling the exosuit and resetting IMUs. In some events, the exosuit was informally removed or adjusted.

The data analyzed for this study were part of a broader protocol in which participants were exposed to five or six exosuit assistive profile blocks in a randomized order. Controller profiles within each block used a sine-impedance approach [15] designed to deliver a peak lifting/ lowering force of: 1) 250/50, 2) 200/50, 3) 150/50, 4) 250/25, 5) 250/100 or 6) 10/10 "slack suit" respectively. These exosuit assisted blocks were included in the ML models. However, participants also completed a no-suit block in which the exosuit was don/doffed by 6 out of 14 participants mid-collection.

Within each block, participants completed 5/6 unique lifting tasks. All participants completed three stoop lifting tasks in which they "kept their legs as straight as comfortable" while lifting a 0, 5 and 10 kg box with dimensions 43 x 28 x 32 cm. The first four participants to enter the study (2 male, 2 female) also completed a 15 kg stoop task. The remaining eight participants completed a 10 kg squat lift instructed to "bend at their knees". These lifts were constrained temporally to a 50-bpm metronome, with seven seconds of rest provided between each lift repetition. Finally, all participants completed a 10 kg freestyle lifting task where they would "lift in whatever way and at whatever speed was natural for them". For each of the lifting types, participants completed five to seven repetitions, with one to two minutes of rest between lifting types. Participant position was constrained by marking the placement of the participant's feet and the box to ensure comfort and consistency between study conditions.

C. Data Processing and Inverse Dynamics

Kinematic and kinetic data were labeled in QTM and post-processed in Visual3D (CMotion Inc., Kingston, ON) in a standardized pipeline [16]. All data were 4th-order low-pass filtered at 6 Hz. Coordinate system axes of the foot, shank, thigh, pelvis, and torso were defined to match anterior-posterior (Y), medial-lateral (X), and axial (Z) directions, respectively. We calculated three-dimensional overall lumbar moments based on a bottom-up inverse-dynamics approach [16]. For estimation, 200 Hz filtered lumbar moment and force plate data and 100 Hz unfiltered IMU data were downsampled to 50 Hz to reduce training/computational complexity.

D. Neural Network Architectures and Training

Our FCNN architecture comprised four hidden layers. The first and last hidden layer consisted of 32 neurons each, while hidden layers two and three each consisted of 128 neurons. To prevent overfitting, all hidden layers included L2 bias, kernel, and activity regularization, with a regularization rate of 0.001. All hidden layers used a rectified linear unit activation. The output layer consisted of three neurons, one for each lumbar moment direction and linear activation. Training was performed using the Adam optimizer [17] with a learning rate of 0.001 and a log-cosh loss function.

The LSTM model consisted of one LSTM layer with 75 units, a hyperbolic tangent (i.e., tanh) activation function and applied kernel and recurrent regularization. The LSTM layer was followed by two fully connected layers, one containing 512 neurons and one containing eight neurons, both of which used a rectified linear unit activation as well as kernel, bias and activity regularization. Both LSTM and fully connected layers used L2 regularization with a regularization rate of 0.005. As for the FCNN, the model was trained using the Adam optimizer with a learning rate of 0.001 and a log-cosh loss function.

We included data from three body-mounted IMUs and two lab-integrated force plates for both models. The IMU orientation was parametrized by Euler angles (Roll, Pitch and Yaw) for which the roll axis approximately corresponded to the principal axis of motion. Moreover, IMUs provided three dimensional local accelerations and angular velocities. We excluded the Yaw angles from the set of features due to unreliable signal quality. Overall, combined with three dimensional GRF signals from each force plate, this led to a total set of 30 input features.

Model training was conducted on 10kg (squat, stoop, and freestyle) and 15kg trials from all but one condition block. Remaining trials with external loads of 0 kg and 5 kg as well as all trials from a randomly selected condition, were excluded (Fig 2). To demonstrate generalizability, our test set included only data from the block and weights held out during training (i.e., pink/5kg and purple/0kg). Input data for both networks were standardized before training. For the FCNN, data were shuffled randomly before training. For the LSTM, the input data were first segmented into sequences of 50 samples with a corresponding single target value (i.e. 3-D LM). Sequences were constructed based on a moving window method with a stride of five samples and the sequences themselves were shuffled before training.

Both networks were trained for at most 100 epochs, with a validation split of 0.2 and batch size of 128. Both models were implemented in python using the *TensorFlow* [18] and *Sklearn* [19] libraries.

E. Statistical Analysis

To assess model performance, two primary outcome measures, Pearson correlation coefficients (r) and root mean squared error (RMSE) were calculated between the true (i.e., OMC-based) and predicted moment at each time point. These two primary outcome measures were compared using a threefactor mixed effect ANOVA comparing the accuracy of estimated lumbar moments between axis (3), model types (2), and whether the training data did or did not include a 15 kg mass (2). Thresholds for significance were Bonferroni corrected for the two primary outcome measures ($\alpha = 0.025$). Significant interactions & main effects were post-hoc tested using Tukey's HSD. Data normality and linearity violations were checked by the Johnson's test function in Minitab 21 (Minitab LLC, State College, PA).

III. RESULTS

A. *Overall Estimation Performance*

For both model types, across the three movement axes, flexion-extension (FE), lateral-flexion (LF) and axial-rotation (AR), lumbar moments were estimated with a low RMSE of 1.58 ± 1.02 Nm and showed excellent correlation with OMC-based values (r = 0.95 ± 0.06) (see Table 1 and Table 2). Accuracy varied by axis, as indicated by an axis main effect ($F(2,60) = 30.2$, $p < 0.001$), which captured that correlations were significantly stronger for FE (r = 0.999 ± 0.002), than correlations for LF (r = 0.94 ± 0.05) and AR (r = 0.93 ± 0.07) (see Fig. 3).

TABLE 1. RMSEs (Nm) across movement planes. FE=Flexion-Extension, LF=Lateral Flexion, AR=Axial Rotation.

	FCNN			LSTM		
Subject	FE	LF	AR	FE	LF	AR
S1	2.86	0.96	0.89	2.59	0.87	1.03
S2	3.14	1.18	0.60	2.98	1.23	0.64
S3	4.28	1.33	0.87	3.73	1.09	0.86
S4	3.72	1.44	0.87	3.52	1.19	0.98
S5	2.21	1.17	0.59	2.02	1.01	0.57
S6	3.04	0.97	0.71	3.39	0.87	0.78
S7	2.50	1.84	0.87	3.15	1.50	0.88
S8	3.18	0.90	0.66	3.06	1.08	0.93
S9	2.81	1.00	0.66	2.43	1.04	0.83
S10	2.50	1.03	0.78	3.22	0.89	0.82
S11	3.18	1.52	0.58	2.58	1.43	0.63
S12	3.11	1.02	0.74	3.55	1.04	0.63
S13	2.11	0.81	0.43	1.73	0.86	0.43
S14	2.10	1.06	0.39	2.29	0.96	0.40

RMSE was significantly higher in the FE direction ($F(2,60) = 296.4$, $p < 0.001$) than for the other axes. However, this finding did not hold upon normalizing the data to their respective moment ranges (FE: 167 ± 38 Nm, LF: 25 ± 8 Nm, AR: 12 ± 6 Nm). Considering that flexion-extension was the principal movement direction among the tasks performed in this study, unsurprisingly, the corresponding normalized RMSEs were lower for FE (1.78 ± 0.44%), than for LF (4.80 ± 1.66%) and AR (6.64 ± 2.82%).

B. *Effect of Model Type*

We found no significant differences between the two model types for both RMSE ($F(1,60) = 0.43$, $p = 0.51$) as well as strength of correlation ($F(1,60) = 0.04$, $p = 0.84$), indicating that incorporating temporal information does not lead to improved estimation performance given the available sensor combination of force plates and IMUs. No model by axes interactions was found ($F(2,60) < 1.22$ & $p > 0.304$)

C. *Effect of External Loads*

To understand whether training on an additional mass besides 10 kg could improve model performance on unseen external loads, we compared the estimation results between four participants who had completed an additional condition with a 15 kg load (W15), to the remaining eight participants who did not (WO15) complete this condition. Interestingly, we found that including this additional external load condition did not statistically impact the strength of correlations ($F(1,12) = 2.14$, $p = 0.169$, W15 r = 0.876 ± 0.148 vs. WO15 r = 0.919 ± 0.104) or RMSE ($F(1,12) = 0.10$, $p = 0.757$, W15 1.58 ± 1.06 Nm vs. WO15 1.47 ± 0.96 Nm).

TABLE 2. Pearson Correlation Coefficients (PCC) across movement planes. FE=Flexion-Extension, LF=Lateral Flexion, AR=Axial Rotation

	FCNN			LSTM		
Subject	FE	LF	AR	FE	LF	AR
S1	1.00	0.97	0.75	1.00	0.98	0.75
S2	1.00	0.84	0.83	1.00	0.82	0.83
S3	0.99	0.99	0.98	0.99	0.99	0.98
S4	1.00	0.99	0.99	1.00	0.99	0.99
S5	1.00	0.90	0.93	1.00	0.92	0.93
S6	1.00	0.93	0.98	1.00	0.94	0.98
S7	1.00	0.85	0.91	1.00	0.89	0.91
S8	0.99	0.97	0.97	0.99	0.97	0.96
S9	1.00	0.98	0.99	1.00	0.98	0.99
S10	1.00	0.92	0.93	1.00	0.94	0.93
S11	0.99	0.96	0.95	1.00	0.96	0.94
S12	1.00	0.97	0.97	1.00	0.98	0.97
S13	1.00	0.98	0.91	1.00	0.97	0.91
S14	1.00	0.83	0.86	1.00	0.88	0.84

IV. DISCUSSION

This study explored two individualized machine learning approaches to estimate lumbar moments in lifting under various external loading conditions in healthy individuals. To this end, our implementation relies on data from laboratory grade force plates and three exosuit integrated inertial measurement units. Overall, our findings show that, following an initial, user-specific model calibration (i.e., training phase), lumbar moments could be estimated with high accuracy on unseen data. This outcome suggests that, once tuned to a user, this approach may offer a quick yet reliable alternative to estimating lumbar moments without the real-time constraints imposed by optical motion capture systems.

Across motion planes, lumbar moments were predicted with comparable correlation strengths but lower error than ranges reported in related work (9-42 Nm) [11], [20]. Unfortunately, comparing performance between studies is difficult as differences could be attributed to variations in sensor inputs, model types, model generalizability (to be discussed), and experimental design, including spatial-temporal constraints. In line with existing work, once normalizing RMSEs to the overall range within each axis,

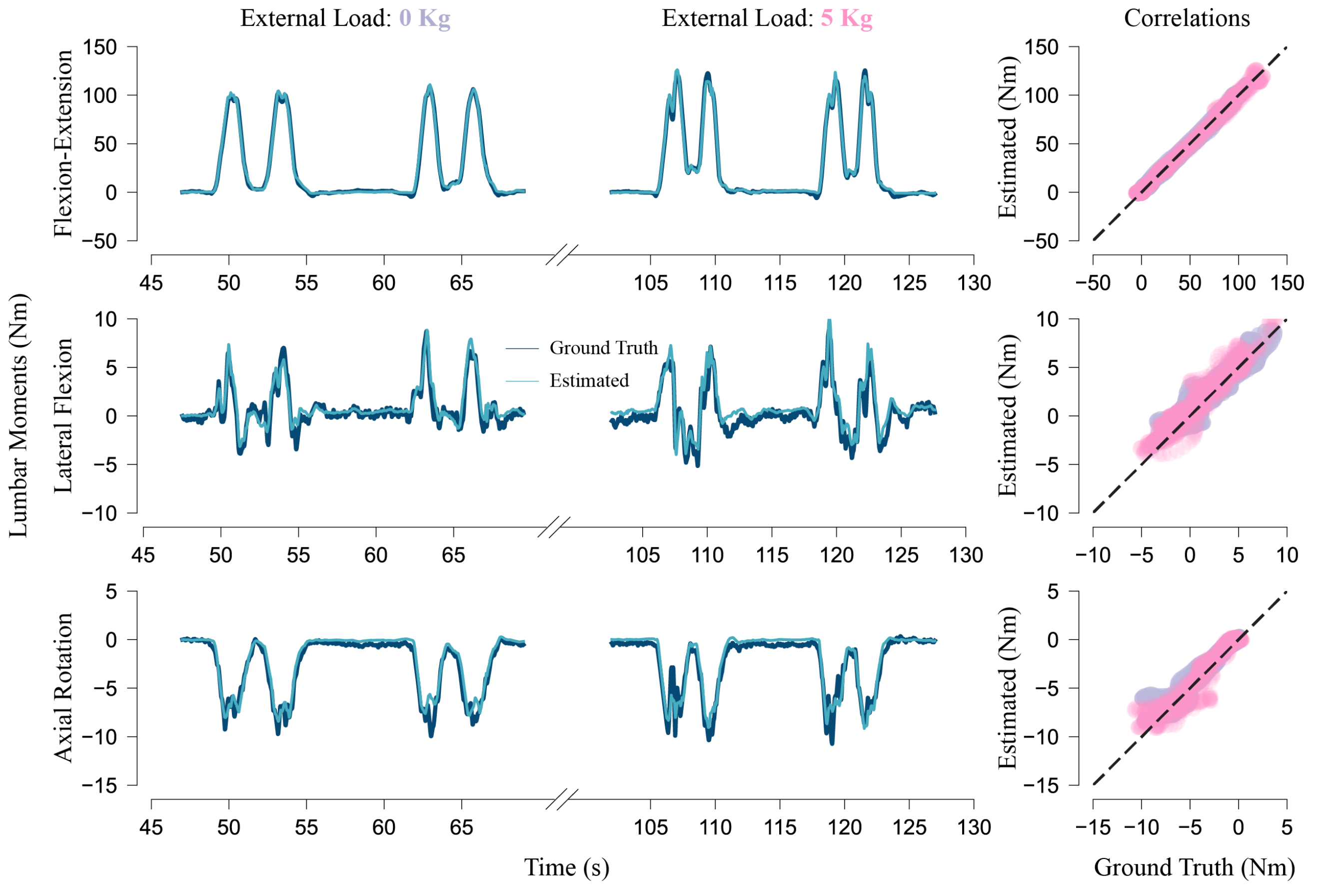

Figure 3. Exemplary estimation and correlation results from one participant. Estimations were made on the 0 kg (left column) and 5 kg (middle column) loading conditions in the test set. For each loading condition true and estimated lumbar moments are shown in each movement direction for two lift cycles. Corresponding correlations are shown in the right column.

moments were predicted with the highest accuracy and correlation in the principal axis of movement [20], [21]. Considering the use case of actuating an exosuit that delivers assistive moments predominantly in flexion-extension high accuracy in this plane would be important for developing reliable, moment-derived control strategies. However, to improve the generalizability of this model future work will likely require additional training to make these predictions robust to off-axis movements.

Within this study, we did not observe significant differences in RMSE or correlation between FCNN and LSTM architectures, implying that, consistent with the relatively few studies that have estimated hip or lumbar kinetics [22], [21], the inclusion of time information has a relatively small effect on estimation accuracy. Considering that error magnitudes were very low overall, non-significant differences appear reasonable and suggest that the combination of low pass filtered force plate and (raw) IMU data holds enough predictive power to learn an instantaneous mapping from sensor inputs to lumbar moments. Future work should establish if LSTM improves performance learning noisy data.

The performance of ML approaches also depends on the level of generalizability a model attempts to achieve. In much of the literature, ML approaches attempt to generalize predictions to unseen participants, reporting RMSEs in the range of 17 - 37 Nm [9]. An improvement over IMU-informed kinetic models that achieve errors of 9- 42 Nm [11], [12], [23]. Such user-agnostic approaches are well justified in the context of estimating spinal loads as a method of risk assessment [5]. Meanwhile, achieving higher accuracies by training models within an individual would be more conducive to control applications, in which estimation inaccuracies could promote device distrust by potentially leading to inadequately delivered assistance. While higher estimation accuracies are noted when using user-specific models (RMSE range 11-30 Nm [10], [11], [20], [22], [24]), it was encouraging to see that our results were obtained using data from an unseen trial in which the IMUs had previously been reset and comprised external loads excluded from the training set. These findings suggest that such an approach could be resilient to IMU repositioning following a user doffing/ donning an exosuit, after performing a simple calibration sequence [7]. Furthermore, this approach suggests that the prediction of overall lumbar moments can be robust to the subtle kinematic and kinetic changes associated with providing exosuit assistance and lifting unseen loads. This is an encouraging result considering future goals to deliver exosuit assistance proportional to overall task demands. However, future studies must characterize whether these findings remain true for between day reliability.

This study was subject to certain limitations that should be considered when interpreting the presented results. As alluded to previously, lumbar moments were estimated on a within-subject basis. While we believe this approach has merit given the anticipated use for moment-informed control applications, a user-agnostic model would alleviate the need for calibrations and processing time imposed by the need for generating individual, OMC based training data [9]. Secondly, this study relied on laboratory-grade, low-pass filtered force plates for 3-dimensional kinetic information. To achieve a nearly real-time, fully ambulatory lumbar moment estimation, future work will need to investigate the potential of wearable alternatives for real-time filtered or unfiltered load detection. Prior work has suggested that force sensitive gloves [8], insoles [9] and measures of muscular effort [4], [11] could be a suitable alternative in this regard. Next, this study considered full time-series lumbar moment waveforms as target data. However, model accuracy could be improved if outlier waveforms were removed [24] which will be considered in future work. Last, despite constructing a test case with reinitialized sensors and unseen external loads, the tasks considered in this study were highly repeatable. Investigating to what extent these approaches generalize to more variable, real-world movements would be another interesting direction to explore.

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