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HYBRID PREDICTIVE MODEL FOR ASSESSING SPINAL LOADS FOR 3D ASYMMETRIC LIFTING

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ABSTRACT

In this study, a hybrid predictive model is used to predict 3D asymmetric lifting motion and assess potential musculoskeletal lower back injuries for asymmetric lifting tasks. The hybrid model has two modules: a skeletal module and an OpenSim musculoskeletal module. The skeletal module consists of a dynamic joint strength based 40 degrees of freedom spatial skeletal model. The skeletal module can predict the lifting motion, ground reaction forces (GRFs), and center of pressure (COP) trajectory using an inverse dynamics based optimization method. The equations of motion are built by recursive Lagrangian dynamics. The musculoskeletal module consists of a 324-muscle-actuated full-body lumbar spine model. Based on the generated kinematics, GRFs and COP data from the skeletal module, the musculoskeletal module estimates muscle activations using static optimization and joint reaction forces through the joint reaction analysis tool. Muscle activation results between simulated and experimental EMG are compared to validate the model. Finally, potential lower back injuries are evaluated for a specific-weight asymmetric lifting task. The shear and compression spine loads are compared to NIOSH recommended limits. At the beginning of the dynamic lifting process, the simulated compressive spine load beyond the NIOSH action limit but less than the permissible limit. This is due to the fatigue factors considered in NIOSH lifting equation.

Keywords: Lifting, Asymmetric lifting, Motion prediction, Lower back injuries, Musculoskeletal injuries.

1. INTRODUCTION

Lower back injury (LBI) is one of the main reasons for work-related musculoskeletal disorders. Lower back and neck pain was the leading cause of disability in 2015 in most countries [1]. The financial impact of LBI is more than \$13 billion in the USA, considering only the direct cost [2]. Several researchers have been working for decades to reduce LBI using experimental or clinical information such as in-vivo or in-vitro data [3, 4]. However, experimental-data-based injury analysis is complicated in an industrial setup as it requires large space, expensive equipment, and trained personnel. Biomechanical models are handy in industrial environments.

Considering the lifting-related tasks, symmetric and asymmetric lifting tasks are common in an industrial setup. During symmetric lifting tasks, the human body's zero moment point (ZMP) stays on the sagittal plane, in contrast, the ZMP moves away from the sagittal plane during asymmetric lifting because of the spinal, shoulder, and hip rotations. This makes the asymmetric lifting tasks more injury-prone for the lower back and requires extra caution.

Researchers used different biomechanical models to assess various manual material handling related tasks. Among them, skeletal models are popular because it is simple and computationally efficient. The skeletal models can be categorized into two-dimensional (2D) and three-dimensional

(3D) models. The 2D models are computationally fast and efficient [5-15]. However, it is incapable of capturing the differences of kinematics and kinetics on both sides of the human body. Therefore, 2D models are compatible with only symmetric lifting-related injury evaluation.

On the other hand, 3D models are computationally slower than 2D models but are suitable for asymmetric lifting tasks, as they can capture the differences of kinematics and kinetics on both sides of the human body [16-20]. In our previous work, we reported a hybrid predictive model for symmetric lifting tasks [26]. However, both types of skeletal models lack muscle and tendon physiology. Muscle and tendon physiologies are required in a biomechanical model for musculoskeletal injury analysis. Dembia et al. [21] developed a predictive pure musculoskeletal tool that can predict squat-to-stand motion. However, musculoskeletal models are complicated, and predictive musculoskeletal models are computationally heavy and time-consuming. It is essential to evaluate the injuries online in an industrial arrangement to get the full benefits of a biomechanical model for the workers' injury assessment. This time-constraint makes it challenging for the researchers to implement predictive musculoskeletal biomechanical models in an industrial setup.

In this study, we extend our previous work to a hybrid predictive model for an asymmetric lifting task and assessing the lower back injuries. The hybrid predictive model is computationally faster than the musculoskeletal model but can assess potential musculoskeletal injuries.

2. HYBRID PREDICTIVE MODEL

The hybrid predictive model has two modules: predictive skeletal module and musculoskeletal analysis module. The predictive skeletal module can predict the lifting motion, GRFs, and center of pressure (COP). The musculoskeletal module estimates muscle activation and joint reaction forces.

2.1 Predictive skeletal module

The predictive skeletal module consists of a 40-degrees-of-freedom (DOF) dynamic-joint-strength-based 3D skeletal model, as shown in Figure 1(a). The model has 6 DOFs for the spine, 7 DOFs for each arm and each leg. The model has 20 DOFs for the upper extremity and 14 DOFs for the lower extremity. The relationships among the joints and links of the 3D model are expressed using the Denavit-Hartenberg representation. The general equations of motion (EOM) of the skeletal model are expressed using Recursive Lagrangian formulation in matrix forms. The EOM of the spatial skeletal model can be expressed as in Equations (1-5) where $i=n, \dots, 1$.

$$\tau_i = \text{tr} \left(\frac{\partial \mathbf{A}_i}{\partial q_i} \mathbf{D}_i \right) - \mathbf{g}^T \frac{\partial \mathbf{A}_i}{\partial q_i} \mathbf{E}_i - \mathbf{f}_k^T \frac{\partial \mathbf{A}_i}{\partial q_i} \mathbf{F}_i - \mathbf{G}_i^T \mathbf{A}_{i-1} \mathbf{z}_0 \quad (1)$$

$$\mathbf{D}_i = \mathbf{I}_i \mathbf{C}_i^T + \mathbf{T}_{i+1} \mathbf{D}_{i+1} \quad (2)$$

$$\mathbf{E}_i = m_i \mathbf{r}_i + \mathbf{T}_{i+1} \mathbf{E}_{i+1} \quad (3)$$

$$\mathbf{F}_i = \mathbf{r}_k \delta_{ik} + \mathbf{T}_{i+1} \mathbf{F}_{i+1} \quad (4)$$

$$\mathbf{G}_i = \mathbf{h}_k \delta_{ik} + \mathbf{G}_{i+1} \quad (5)$$

where $\text{tr}(\cdot)$ is the trace of a matrix, \mathbf{D}_i is the recursive inertia and Coriolis matrix, \mathbf{I}_i is the inertia matrix for link i , \mathbf{g} is the gravity vector, \mathbf{E}_i is the recursive vector for the gravity torque calculation, m_i is the mass of link i , \mathbf{r}_i is the center of mass of link i , $\mathbf{f}_k = [f_{kx} \ f_{ky} \ f_{kz} \ 0]^T$ is the external force applied on link k , \mathbf{F}_i is the recursive vector for the external force-torque calculation, \mathbf{r}_k is the position of the external force in the local frame k , δ_{ik} is Kronecker delta, \mathbf{G}_i is the recursive vector for the external moment torque calculation, $\mathbf{h}_k = [h_x \ h_y \ h_z \ 0]^T$ is the external moment applied on link k , $\mathbf{z}_0 = [0 \ 0 \ 1 \ 0]^T$ is for a revolute joint, $\mathbf{z}_0 = [0 \ 0 \ 0 \ 0]^T$ is for a prismatic joint. The starting conditions are $\mathbf{D}_{n+1} = [\mathbf{0}]$, $\mathbf{E}_{n+1} = \mathbf{F}_{n+1} = \mathbf{G}_{n+1} = [\mathbf{0}]$. n denotes total DOFs of the model. Details can be found in [22].

For 3D skeletal asymmetric lifting prediction, the design variables (\mathbf{x}) are cubic B-spline control points of joint angle profiles. The objective function J is the summation of normalized joint torque squares. The objective function can be expressed as in Equation (6):

$$J(\mathbf{x}) = \int_0^T \sum_{i=7}^n \left(\frac{\tau_i^U - \tau_i^L}{\tau_i^U - \tau_i^L} \right)^2 dt \quad (6)$$

where τ_i^L and τ_i^U are the i th lower and upper dynamic joint torque limits, respectively, T represents the total time for the lifting task. The asymmetric lifting task is formulated as a nonlinear programming (NLP) problem. The optimizer tried to find the optimal design variables \mathbf{x} to minimize a human performance measure J , subject to physical and task constraints. In this formulation, the time-dependent constraints are joint angle limits, dynamic joint torque limits, dynamic-balance constraint, foot contacting position, and collision avoidance. The time-independent constraints are initial and final box locations, initial and final static conditions, initial, mid-time, and final postures, and GRF constraints. Details about the optimization formulation of skeletal model can be found in [20, 23].

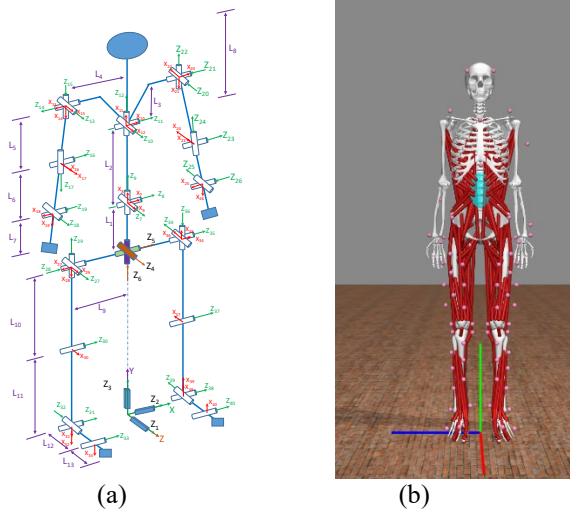


FIGURE 1: (a) Skeletal model (b) musculoskeletal model

2.2 Musculoskeletal analysis module

The musculoskeletal analysis module consists of an OpenSim full-body lumbar spine (FBLS) musculoskeletal model, as shown in Figure 1(b). The model has 30 DOFs, 21 segments, and 324 musculoskeletal actuators [25]. The model was scaled according to the subject's anthropometric data. The model was modified according to [24] to make it suitable for the static optimization during lifting tasks. Before importing the predicted joint angles, GRFs, and COP into the musculoskeletal model, the coordinate system was transformed so that the skeletal and musculoskeletal model's coordinate systems match with each other. The static optimization tool in OpenSim is used to generate muscle activation and forces. The static optimization minimizes the muscle activation, subject to the muscle-torque equilibrium constant. The joint reaction analysis tool in OpenSim can estimate compressive and shear joint reaction forces of the lumbosacral (L5-S1) spine joint by solving the Newton-Euler equation where all the translational and rotational dynamics of a joint are presented. The details about the coordinate transformation, static optimization and joint reaction force analysis can be found in [26].

3. EXPERIMENTS

The motion predictions of the skeletal module for both symmetric and asymmetric liftings were validated in our previous studies [20, 26]. The muscle activations for symmetric lifting were also validated in [26]. In this study, the muscle activations were collected to validate the asymmetric lifting prediction. The subject for the asymmetric lifting experiment was a 31-year-old male, 1.69 m tall, and with a mass of 63.5 kg. The experiment was approved by the IRB of Texas Tech University. The motion capture data was collected by 8 overhead Eagle-4 cameras (Motion Analysis Corp., Santa Rosa, California, USA) at 100 Hz. The GRF data was collected using a pair of Bertec force plates (Bertec, Columbus, Ohio, USA) at 2500 Hz. The electromyography (EMG) activities of vastus medialis and latissimus dorsi muscles were recorded using Delsys Trigno EMG sensors (Delsys Inc., Natick, Massachusetts, USA) at 2500 Hz. EMG activities were normalized to maximum-voluntary-contractions (MVCs) for all muscles. The lifting was repeated three times. To reduce the fatigue effect, the subject was given enough rest period between two consecutive liftings [27]. The subject was instructed to lift a 7 kg box and put it on a table at the left side from the ground, as shown in Figure 2.



FIGURE 2: Asymmetric lifting experimental setup

4. RESULTS AND DISCUSSION

The NLP problem was solved using an Intel(R) Core (TM) i7-8650U CPU @ 1.90GHz and 16 GB RAM laptop computer. It took 42.01 seconds CPU time for the SNOPT to find the optimal solution for the 7 kg asymmetric lifting optimization problem. Typically, it takes minutes to hours for a musculoskeletal model to predict a human motion [21]. The hybrid model predicts lifting motion and muscle activities faster than other musculoskeletal models. This will help us to implement a real-time musculoskeletal injury analysis tool for an industrial setup.

The snapshot of the predicted asymmetric lifting motion is presented in Figure 3(a). The snapshot of lifting motion in OpenSim after the static optimization is presented in Figure 3(b).

To validate our model, we compare two muscles: one from the lower extremity and one from the upper extremity. The lower extremity muscle is the vastus lateralis, an important muscle in the quadriceps. The upper extremity muscle is the latissimus dorsi, the largest muscle in the upper extremity. The comparison between estimated muscle activations and EMG is presented in Figure 4.

The generated shear and compressive forces, using the OpenSim joint reaction Analysis tool, are presented in Figure 5. The recommended limits to avoid injury for both shear and compressive forces are also presented in the same picture.

EMG data provides information on the activation pattern of a muscle. The magnitude, pattern, and phase changes of the predicted muscle activations for asymmetric lifting agreed well with EMG data for the vastus lateralis (Figure 4 a and b). There are some discrepancies for the latissimus dorsi (Figure 4 c and d). The muscle activation of left latissimus dorsi during 40%-80% of the lifting task, and right latissimus dorsi from 80%-100% of the lifting task are higher than the EMG. Other than that, the predicted muscle activations are close to the EMG data.

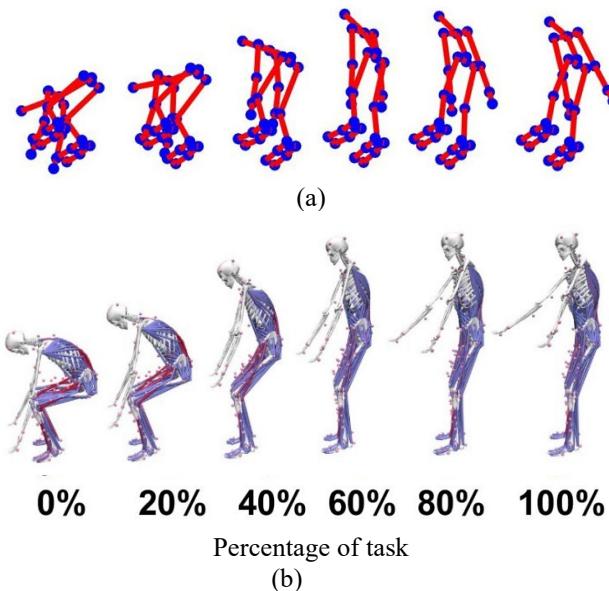


FIGURE 3: Snapshots of 7 kg asymmetric weight lifting task: (a) Predictive skeletal lifting motion, (2) musculoskeletal lifting motion in OpenSim

The asymmetric lifting task requires spinal, hip, and knee rotations, which move the ZMP away from the sagittal plane to the left side of the coronal plane. To stabilize the movement while putting the box on the left side table, it requires extra forces from muscle and tendon. As a result, the muscle activation of the left vastus lateralis (Figure 4a) is higher than that of right vastus lateralis (Figure 4b).

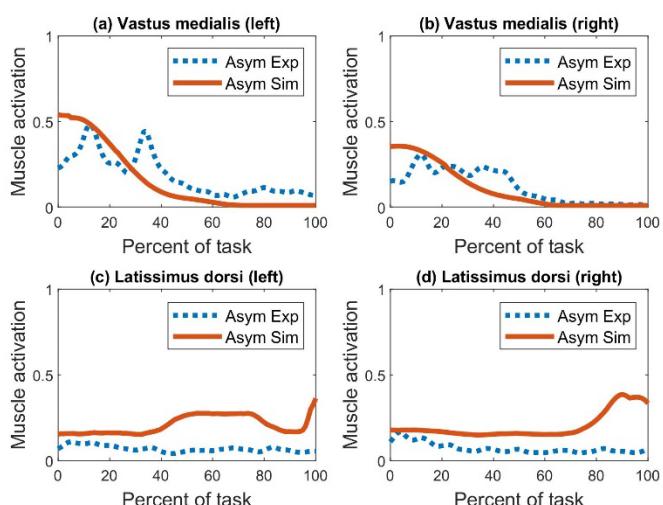


FIGURE 4: Muscle activations during asymmetric lifting

According to the National Institute of Occupational Safety and Health (NIOSH) [28], the biomechanical compressive forces on the lumbosacral joint (L5-S1) are tolerable up to 3400 N (350 kg) for most of the young and healthy workers. This limit is called the action limit. According to the same source, the

compressive forces for more than 6400 N (650 kg) are not tolerable for most of workers. This limit is called the maximum permissible limit. The recommended shear force limit on the L5-S1 joint for occasional lifting tasks (≤ 100 liftings/day) is 1000 N and for repetitive lifting tasks (100-1000 liftings/day) is 700 N [29, 30].

For the asymmetric lifting, the shear force stayed above the recommended shear force limit (100-1000 liftings /day) from the beginning to 35% of the lifting task (Figure 5a). It stayed above the recommended shear force limit (< 100 liftings /day) from the beginning to about 20% of the lifting task. The compressive forces stayed more than the NIOSH recommended action limit from 5% to around 18% of the lifting task (Figure 5b) but stayed below the NIOSH maximum permissible limit throughout the lifting task.

The initial high shear and compressive forces for the asymmetric lifting task are expected as sometimes the subject stayed inclined forward to lift a box and create a higher moment with respect to the ZMP. The subject should avoid such motion as much as possible to avoid any potential lower back injury. In addition, NIOSH recommended limits do not consider the dynamic effects, and they are all static situations. Also, the NIOSH lifting equation considers at least one lift in every five minutes (12 liftings/ hour) for the action limit and maximum permissible limit. In this study, the predicted lifting motion is a one-time lifting. Fatigue is not considered in this study, and this makes the spine loads higher than the NIOSH recommended action limit.

The rotation of the spine and varying compressive and shear loads on the spine joint make the asymmetric lifting tasks more injury-prone than symmetric lifting tasks. It is necessary to be careful and reduce the allowable hand load during asymmetric lifting tasks. This suggestion depends on the individuals. Heavier individuals may have higher spinal compressive and shear forces at low box weight on hand [31].

There are some limitations in this study.

1. Static optimization does not accurately consider the co-contraction of antagonistic muscles [32]. That may affect the spinal compressive and shear force results. Also, OpenSim does not consider the deformation of bones during joint reaction force calculation.

2. The comparison in this study is only for younger subjects. Older adults generally have decreased muscle strength. It is reported that the strength and total muscle cross-sectional area reduce by about 20-40% between the ages of 20 and 60 years [33]. The percentile of dynamic joint strength in the skeletal model can be adjusted for older adults. Also, the musculoskeletal model's muscle strength needs to be adjusted to make the model suitable for older adults' injury analysis.

3. This predictive model is for one-time lifting. Fatigue has not been considered in the model.

Although this study has some limitations, it gives us a lot of internal information such as muscle activations and joint reaction forces during the investigation of asymmetric lifting tasks. This information is crucial for injury analysis but not feasible to get from in-vivo experiments.

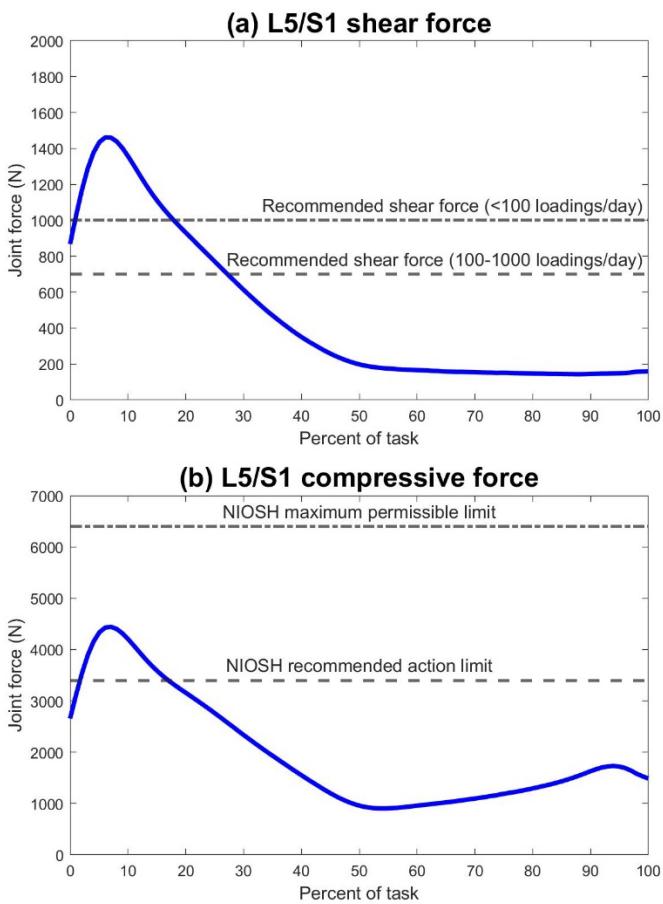


FIGURE 5: (a) Lumbosacral (L5-S1) joint shear force, and (b) compression force for asymmetric lifting

5. CONCLUSION

In this study, we studied the asymmetric lifting task using the hybrid model and assessed potential lower back injuries. The hybrid model predicted the 3D asymmetric lifting motion, GRFs, muscle activations, and joint reaction forces. Asymmetric lifting tasks involve spinal rotation and moment. In addition, they require extra muscle activations to balance the body, which creates higher joint reaction forces. The asymmetric lifting tasks could be analyzed using the developed hybrid model for injury prevention.

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