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MUSCLE FORCE PREDICTION IN OPENSIM USING SKELETON MOTION OPTIMIZATION RESULTS AS INPUT DATA

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ABSTRACT

This paper describes an integrated approach to predict human leg and spine muscle forces during lifting by integration of a predictive skeletal model with OpenSim. The two-dimensional (2D) skeletal lifting motion is first predicted by using an inverse dynamics optimization method. Then, the prediction outputs, including joint angle profiles, ground reaction forces, and center of pressure, are incorporated in OpenSim biomechanics software to analyze muscle forces for lifting. Therefore, the integrated approach has predictive capability on musculoskeletal level. By using this method, we can predict and analyze muscles forces for heavy weight lifting motion which is difficult to simulate directly using a 3D musculoskeletal model.

Keywords: Motion prediction, inverse dynamics optimization, muscle force, OpenSim, lifting.

1. INTRODUCTION

Manual material handling is one of the main reasons for workplace injuries and pains. The consequence of lifting weight exceeding a person's capability could lead to serious muscle injuries [1]. But it is not feasible to determine the maximum lifting weight and its consequences by practical experiments. Predictive simulation based on experimental data can help us to find out the maximum lifting weight [2] and its muscle related consequences. However, it is complicated and time consuming to directly simulate and analyze three-dimensional (3D) muscle model.

For predictive modeling, there are skeletal and musculoskeletal models in the literature. Skeletal models are computationally efficient, but only works in joint space [3, 4]. In contrast, musculoskeletal models can reveal more muscle information, but it requires more computational effort [5]. Recently, there are some progress in predictive musculoskeletal modeling, such as mixed forward and inverse method [6] and direct collocation method [7, 8]. These methods still require hours of CPU time to optimize a 3D musculoskeletal model due to its complexity.

OpenSim® uses computed-muscle-control (CMC) method, which is a control-based forward dynamics simulation approach [9]. This method can easily track the captured motion to compute muscle excitation, activation, moment arm, and muscle-tendon length. Although it is an effective approach, it tracks experimental data and lacks predictive capability. The objective of this study is to combine the predictive skeletal model and OpenSim model to predict muscle forces. The integrated method has two steps: First, the lifting motion, ground reaction forces (GRF) and center of pressure (COP) are predicted using a skeletal model in joint space. Secondly, the predicted data are used as inputs for OpenSim to simulate the lifting motion and analyze muscle forces.

2. PREDICTIVE SKELETON MODEL SIMULATION

A two-dimensional (2D) skeletal model with 10 degrees of freedom (DOFs) is used in this study. The three global DOFs include two translational and one rotational joints. The seven physical joints are spine, shoulder, elbow, hip, knee, ankle, and metatarsal joints. Anthropometric data are calculated from GEBOD software [10] using the subject's height and weight as the input data. Recursive Lagrangian dynamics is used to set up the equations of motion for the biomechanical system [11].

In this study, the 2D symmetric maximum weight lifting motion is simulated using an inverse dynamics optimization method [12]. The lifting problem is formulated as an optimization problem by maximizing the box weight (W) and considering the joint angle profiles (discretized B-spline control points) as design variables subject to following constraints:

Joint angle limits,

$$\boldsymbol{q}^L \leq \boldsymbol{q}(t) \leq \boldsymbol{q}^U \tag{1}$$

where $\boldsymbol{q}^L$ and $\boldsymbol{q}^U$ are the joint angle lower and upper bounds.

Joint torque limits,

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$$\boldsymbol{\tau}^L \leq \boldsymbol{\tau}(t) \leq \boldsymbol{\tau}^U \qquad (2)$$

where $\boldsymbol{\tau}^L$ and $\boldsymbol{\tau}^U$ are the joint torque lower and upper bounds.

Balance condition,

$$p_{ZMP}(\boldsymbol{q}, t) \in FSR \qquad (3)$$

where p_{ZMP} is the zero-moment-point (ZMP) location, and FSR represents the foot support region.

Feet contacting positions,

$$p_{foot}(\boldsymbol{q}, t) = p_{foot}^E \qquad (4)$$

where p_{foot} is the calculated foot position and p_{foot}^E is the measured experimental foot position.

Initial and final hand (box) locations,

$$p_{hand}(\boldsymbol{q}, t) = p_{box}^E(t); \qquad t = 0, T \qquad (5)$$

where p_{hand} is the calculated hand position, p_{box}^E is the experimental box position, and T is total time.

Posture constraints from experiment,

$$|\boldsymbol{q}(t) - \boldsymbol{q}^E(t)| \leq \varepsilon; \qquad t = 0, \frac{T}{4}, \frac{T}{2}, \frac{3T}{4}, T \qquad (6)$$

where $\boldsymbol{q}^E$ is the experimental joint angle, $\varepsilon = 0.15$ rad.

The predicted lifting motion is depicted in Fig. 1. The predicted joint angles and GRF profiles are shown in Fig. 2.

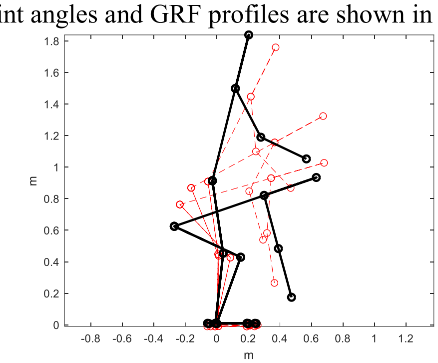


Fig. 1. Snapshots of the predicted lifting motion

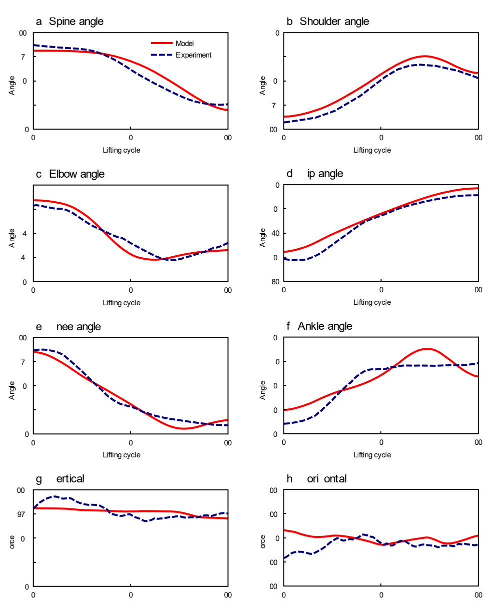


Fig. 2. Predicted joint angles and GRF for the maximum weight lifting

3. OPENSIM MODEL SIMULATION

OpenSim® is an open-source software package that can be used to build, exchange, and analyze computer models of the musculoskeletal system and dynamic simulations of movement [13]. Some of the most useful features of OpenSim are scaling, inverse kinematics, inverse dynamics, CMC analysis. In this study we have used a leg muscle model [14] and a spine muscle model [15] in OpenSim to predict muscle forces.

3.1 Computed muscle control algorithm

CMC tool is a graphical user interface (GUI) to control the input and output of the algorithm. The Fig. 3 shows the required inputs and outputs for the CMC tool [13]. The input data has three parts: CMC setup, experiment, and OpenSim model. The output data also has three parts: muscle and model states, forces, and controls (muscle excitation).

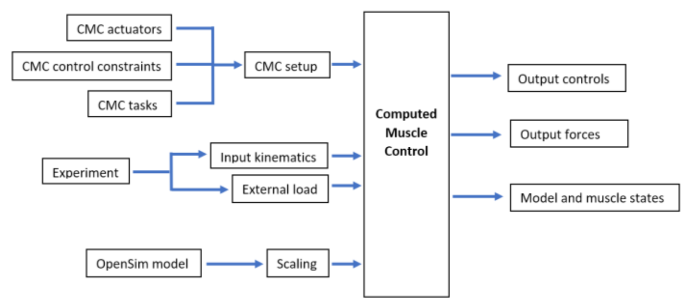


Fig. 3. Inputs and outputs of CMC tool

CMC algorithm computes muscle excitation levels that will drive the generalized coordinates such as joint angles of a dynamic musculoskeletal model towards a desired kinematic trajectory in the presence of applied external forces. The overall flow chart of CMC is depicted in Fig. 4 and illustrated below [9].

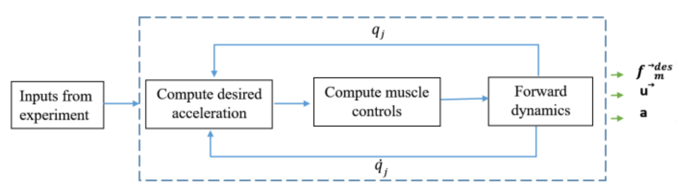


Fig. 4. Computed muscle control (CMC) flow chart

The first step of CMC is to compute desired accelerations ($\ddot{q}_j^{des}(t + \Delta T)$) based on Proportion-Derivative (PD) control. The time interval ΔT should be short enough to allow adequate control, but long enough to allow muscle forces to change. ΔT is typically chosen as 0.01 second.

From the desired accelerations $\ddot{q}_j^{des}(t + \Delta T)$, the desired torque ($\boldsymbol{\tau}^{\text{des}}$) can be found from equations of motion using inverse dynamics. Static optimization distributes net joint torque into muscle-tendon forces at the time $t + \Delta T$. The next step is to compute the muscle excitations based on the calculated muscle-tendon forces and state variables using root-finding algorithm.

The final step of CMC algorithm is to use computed control (muscle excitations) to conduct a standard forward dynamic simulation. Muscle excitations, which we obtained from the muscle-tendon forces, will be used in forward dynamics to drive the simulation model using one-step numerical integration.

4. RESULTS AND DISCUSSION

By inputting the simulation data (joint angle, GRF, COP profiles) into OpenSim musculoskeletal model, we can get the same exact motion of 2D simulation. Then in OpenSim, we can analyze the change of joint and muscle information, e.g., active fiber force, passive fiber force, tendon force, fiber length, and tendon length for the same motion.

After transferring the kinematics and external force data from predictive model to OpenSim, the motion in OpenSim is presented in Fig. 5.

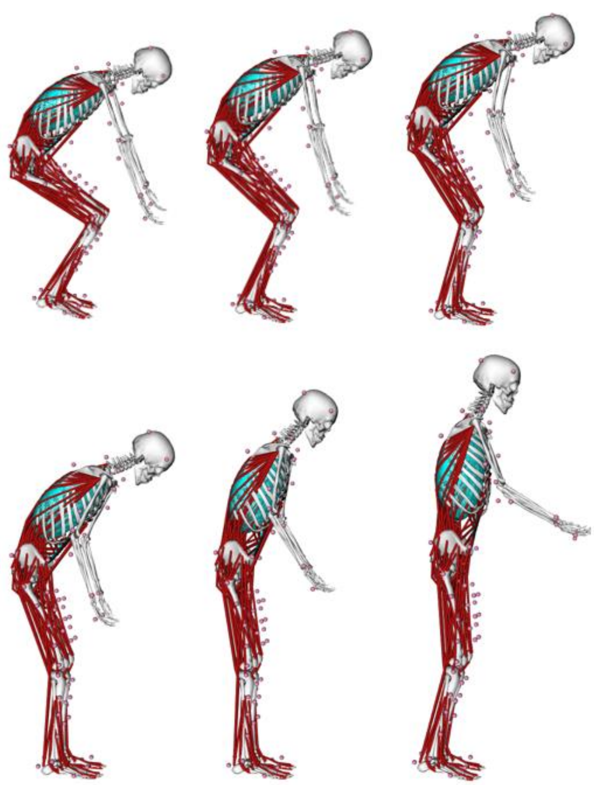


Fig. 5. Snapshots of lifting motion in OpenSim

Comparing Fig. 5 with Fig. 1, it is shown that the motions are similar. Next step is to analyze the muscle forces during lifting.

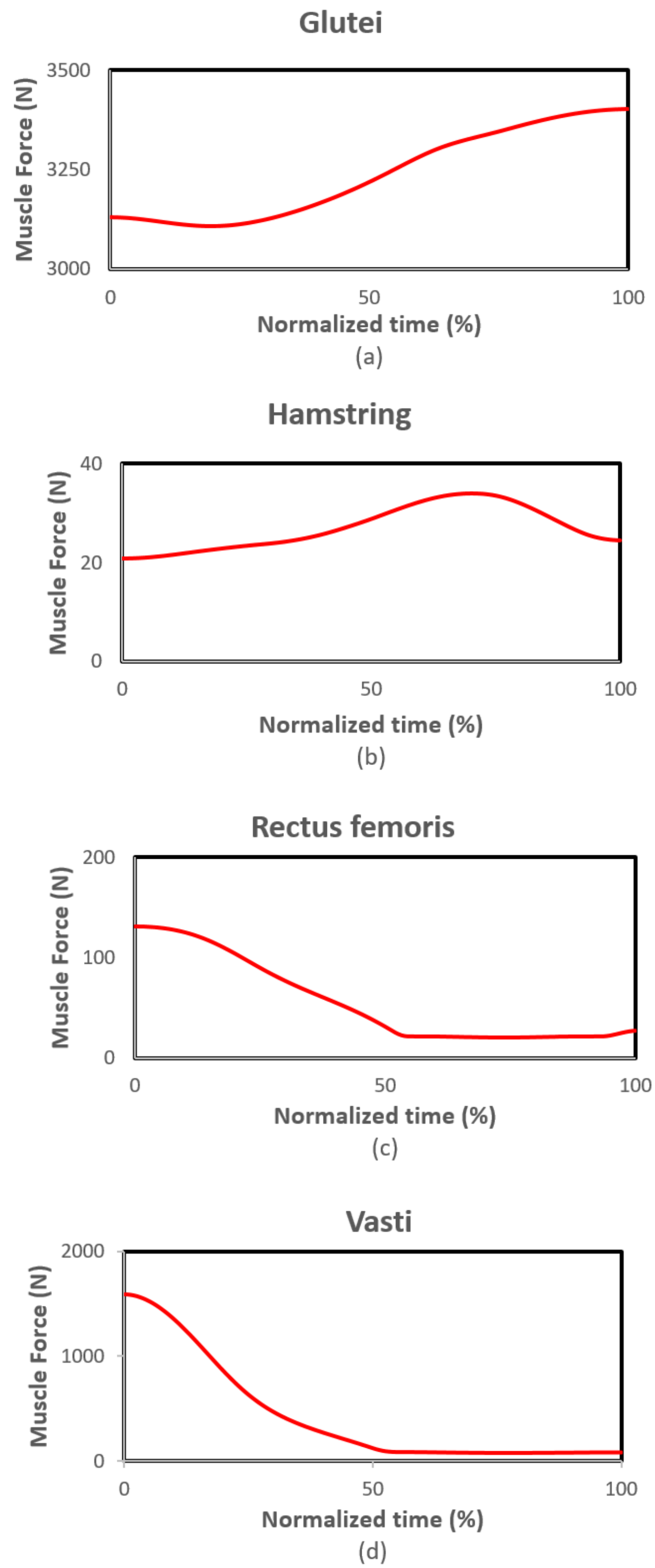
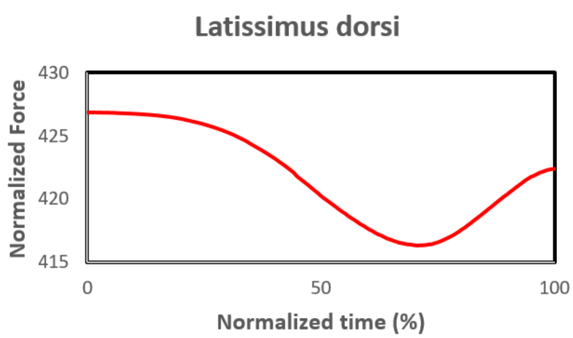


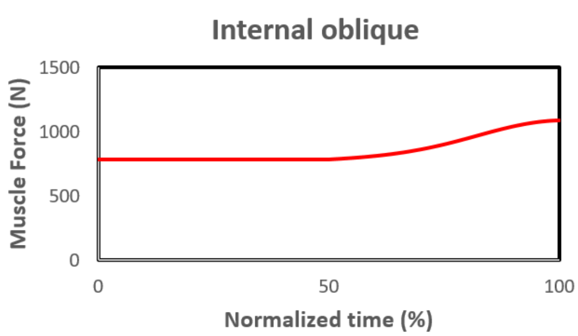
Fig. 6. Leg muscle forces during lifting

Glutei muscles take significant amount of load during lifting. Knee joint extension is almost completed at around 60% of the lifting time. As a result, the load is carried out mainly by hip and spine muscles after that. Glutei muscles help to hold the body and give extra force at the end of lifting (Fig. 6a). The change of force in glutei muscles is between 3100 N to 3400 N. There is no significant change in hamstring muscle force during this lifting motion (Fig. 6b). At the initial stage of motion, rectus femoris muscles become activated and support the leg joint during lifting (Fig. 6c). Like rectus femoris, vasti muscles are activated initially and generate significant initial force until the knees are extended. These muscles generate about 1600 N force initially (Fig. 6d).

During the lifting motion, there is no significant change in the muscle force of latissimus dorsi (Fig. 7a). It changes between 415 N to 430 N. On the other hand, internal oblique muscles give a huge amount of support during motion. The change of muscle force in internal oblique is between 800 N to 1200 N (Fig. 7b). Internal oblique muscles start to support the weight when the elbow starts to flex.



(a)



(b)

Fig. 7. Spine muscle forces during lifting

5. CONCLUSION

In this paper, we presented an integrated approach to analyze muscle forces of a 3D musculoskeletal model in OpenSim using a 2D skeletal predictive model. The important leg and spine muscle forces during lifting were demonstrated in OpenSim.

It has been shown that during the maximum weight lifting motion, glutei and vasti muscles from leg and internal oblique muscles from spine generated significant amount of forces. By using our 2D skeletal predictive model and interfacing it with the 3D musculoskeletal model, we can predict and analyze muscle forces for heavy weight lifting motion which is difficult to simulate directly using a 3D musculoskeletal model.

One limitation of our model is that the 2D predictive model contains only sagittal plane data of 3D musculoskeletal model which gives only flexion, extension, dorsiflexion and plantarflexion movements. Frontal and transverse plane movements like abduction, adduction or internal rotation and its effect on muscle forces cannot be analyzed.

Our future work is to upgrade the 2D skeletal predictive model to 3D model so that we can predict and analyze muscle forces for all kind of movements using the proposed method. In addition, rigorous experimental validation of the predicted muscle forces will be conducted using electromyography (EMG) sensors.

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