Predicting Gait Adaptation due to Exoskeleton Assistance using Musculoskeletal Model derived from Videos

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***Abstract*— The use of musculoskeletal model to analyze the user-exoskeleton interactions can generate exoskeleton assistive to improve human performance or rehabilitate impaired patient mobility. Nonetheless, the distortion of the video-derived musculoskeletal model prevents its application in clinical practice. This study aims to investigate the robustness and accuracy of the video-derived musculoskeletal model in the presence of model distortion uncertainty through sensitivity analysis. We introduced changes in environmental conditions, such as inclination and backpack loads, analyzed trends in walking gait, and compared them with experimental data to verify validity. Our preliminary analysis suggested that the kinematic data acquired by the lightweight mobile phones have musculoskeletal reliability and are feasible for predicting gait adaptation with exoskeleton assistance.**

I. INTRODUCTION

In recent years, the use of exoskeleton to assist human motion has become a promising approach to enhance human performance or rehabilitate the mobility of impaired patients [1]. The purpose is to reduce metabolic consumption during human motion or to provide assistive power to mobility impaired patients. However, exoskeleton assistance has challenges in analyzing user-exoskeleton interaction, such as the high redundancy of the musculoskeletal system in humans [2, 3] and significant individual differences [4, 5], making it challenging to derive the trivial solution for assistance strategy and adaptation to the individual.

The musculoskeletal model as middleware can manage various components in complex user-exoskeleton interactions and analyze the system to derive assistive strategies [6].To identify the assistive strategy suitable for the subject, human-in-the-loop optimization tuned the control parameters through the musculoskeletal model during the subject's movement [7, 8], but its instability in the optimization stage may cause discomfort to subjects with unhealthy legs. In contrast to optimizing the assistive strategy for subject on-line, predictive simulation allows the biomechanics analysis under different physiological conditions [9, 10]. The musculoskeletal model was used to forward simulate the walking gait and iteratively optimize the controller parameters.

Although assistive strategies based on musculoskeletal model are promising approaches, the accuracy of muscle strength leads to challenges when applied to clinical practice [11]. Calibration of muscle strength required the use of musculoskeletal model and kinematics data from motion capture systems [12, 13]. Nonetheless, the complex configuration and high cost of the sensor, camera and treadmill make it difficult to use in clinical practice [14-16]. Using mobile phone cameras to estimate kinematics is another promising way. For example, OpenCap [17] was used to estimate the coordinates of 3D anatomical markers on the subject's motion trajectory through multiple mobile phones. However, distortions in the video-derived musculoskeletal model may amplify the abnormalities in muscle strength and walking gait, such as interference from light or the object's shape.

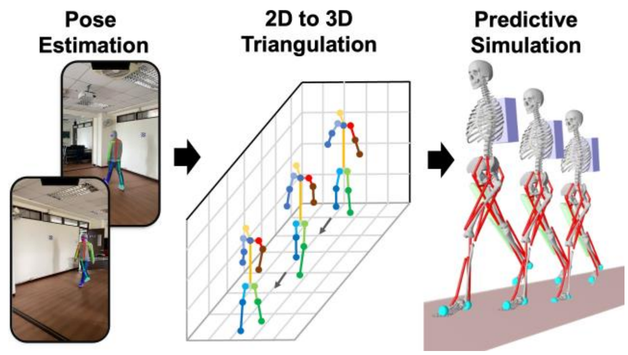

Figure 1. Schematic of the musculoskeletal model derived from the 2D pose estimations then adding exoskeleton assistance. The potential distortion of the model was analyzed by adding ground inclination and backpack loads to investigate the effect of muscle strength and walking gait adaption.

Given the promising clinical practice of the use of mobile phones acquired kinematic data for exoskeleton assistance, it is essential to validate the robustness and accuracy of their muscle strength and gait adaptation. In this study, we aim to investigate the impact of distortions in the video-derived musculoskeletal model on walking gait through sensitivity analysis. To amplify and observe the effects of distortion implied in the model, we analyzed walking gait adaptation by increasing ground inclination and backpack loading, as previous literature has shown significant changes in lower-limb joints and muscle activation [18]. Our preliminary analysis suggests that gait adaptations generated from video-derived musculoskeletal model have reliability in kinematic and kinematic trends and are feasible for estimating muscle strength and gait adaption with exoskeleton assistance.

II. MATERIALS AND METHODS

A. Participants and Video Pre-processing

A healthy subject (age = 22, Body Mass Index = 27.4 kg/m^2) was enrolled for the study. Two iPhone 13 cameras were used to acquire motion videos. To detect 3D anatomical markers positions [19] from the walking motion, the software of OpenCap was used to conduct video pre-processing, such as time synchronization and pose feature extraction.

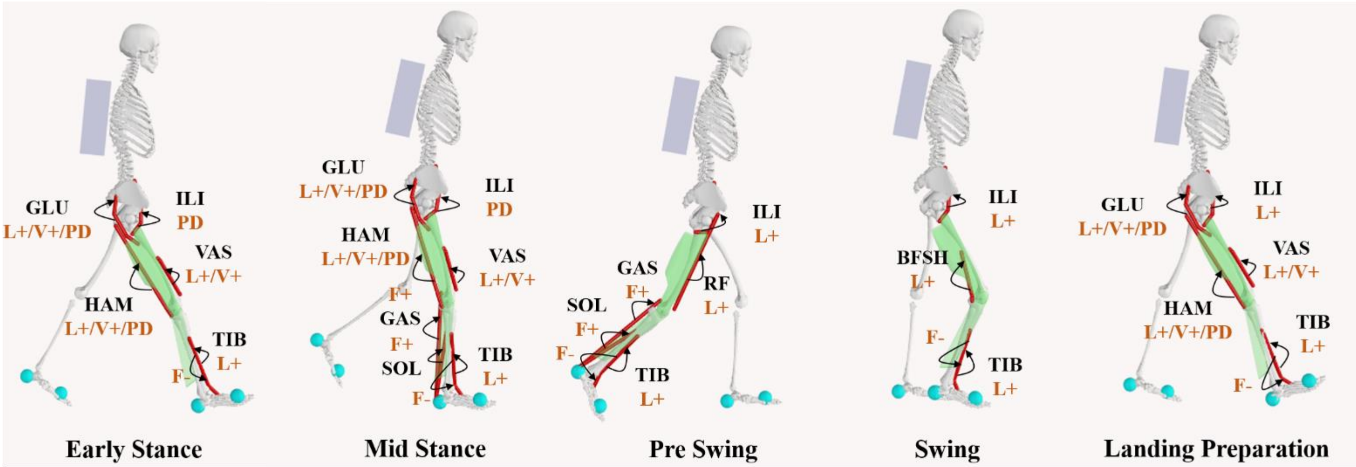

Figure 2. With the addition of the knee exoskeleton (green) and backpack load (blue), the musculoskeletal model determines muscle excitation during the gait cycle through low-level control. Muscle excitation is regulated by normalized muscle fiber length (L), muscle contraction (V), normalized tendon force (F), and proportional-derivative (PD) as feedback to the controller. Positive and Negative feedback of the controller is denoted by (+) and (-) respectively. The contact spheres on the toe and heel of each foot detect the ground reaction force to determine the gait cycle.

As shown in **Fig. 1**, the 2D video keypoints detected by OpenPose [20] were triangulated to calculate twenty 3D tracker positions, which were time-synchronized through cross-correlation. Then, the 3D positions of forty-three anatomical markers were predicted from the previous twenty triangulated 3D trackers using the well-trained long and short-term memory (LSTM) network included in OpenCap.

B. *Muscle Strength Estimated from Videos*

The muscle strengths in the video were estimated biomechanically, we employed a reduced lower-limb muscle model with nine degrees of freedom actuated by sixteen Hill-type tendon units [21] adapted from the gait model included in OpenSim [6], as shown in **Fig. 2**. The added knee exoskeleton (green) provided a maximum of 50 N.m assistive torque to the knee and changed the body mass distribution with a 5 kg backpack load (blue). Then, to fit the musculoskeletal geometry of subjects, we used the OpenSim linear scaling tool to minimize the error between two 3D anatomical marker positions, one predefined on the reduced lower-limb muscle model, and the other calculated from OpenCap. Muscle strengths were calculated *via* OpenSim's muscle analysis tools, as shown in **Fig. 2**, with each muscle showing different activations during walking. The ground contact forces were calculated using the interaction between the contact spheres at the toe and heel of each foot and the ground through the Hertz/Hunt-Crossley contact model [22]. The calculated contact forces were used to detect the gait cycle.

C. *Gait Adaptation Regulated via Reflection Controller*

For the adaptation of walking gait with changing inclination in the environment, we used a reflection-based walking controller to generate time-varying muscle excitation [23]. **Fig. 2** showed the laws of the reflex controller for rectus femoris (RF), hamstring (HAM), glutes (GLU), iliopsoas (ILI) , vastus (VAS), gastroc (GAS), soleus (SOL), and tibia (TIB) muscles.

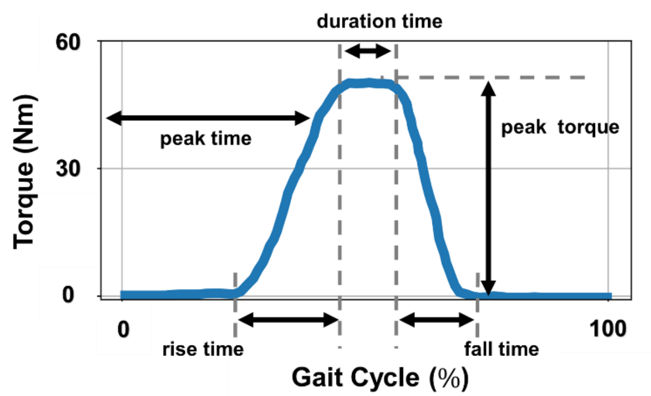

Figure 3. Knee flexion assistive torque, defined by parameters: peak time, duration time, rise time, fall time and peak torque.

Each muscle excitation can be modulated by combining muscle contraction (V), normalized muscle fiber length feedback (L), normalized tendon force (F), and proportional-derivative (PD) control. For example, in early stance of muscle VAS, increasing (L) and (V) will increase muscle excitation (positive feedback). Detailed equations can refer to the defined control laws [23]. The control law for the assistive torques applied by the exoskeleton is parameterized as a function of the time and torque. As shown in **Fig. 3**, there were five parameters: rise time, peak time, duration time, fall time, and peak torque. And the gait cycle percentage was determined by the contact forces between the toe and heel of each foot and the ground as estimated by the Hertz/Hunt-Crossley contact model. Both the reflection control parameters and the assistive torque parameters will be optimized using the covariance matrix adaptation method [24]. The optimization minimizes the metabolic cost [25] at the selected minimum speed and avoids knee hyper-extension by penalizing the forces. The controller and optimization were implemented and executed with SCONE [26], using OpenSim for forward simulation.

III. RESULTS

In the experiments, we first present the predicted simulations through environmental slope changes to show the sensitivity and tread of muscle and walking gait. Then we validated the accuracy of the predictive simulations by comparing with experimental data. Finally, we present the gait adaptation due to exoskeletal assistance based on the parameters that meet the validation.

A. Simulation of Gait Adaptation at Different Slopes

Intuitively, as the incline increased, the angle of ankle contact with the ground became increasingly flexed, and the range of motion of the hip joint became decreasing. In addition, muscle activation also increased with the increase of inclination. The experimental results in **Fig. 4** showed that the simulation results have the similar trends. This implied that the video-derived musculoskeletal model has good reliability to the kinematics and kinetics of humans walking on the flat or inclined ground. The anomalies amplified by the model distortion were insufficient to affect the changing trends in joint angles and muscle strengths in motion.

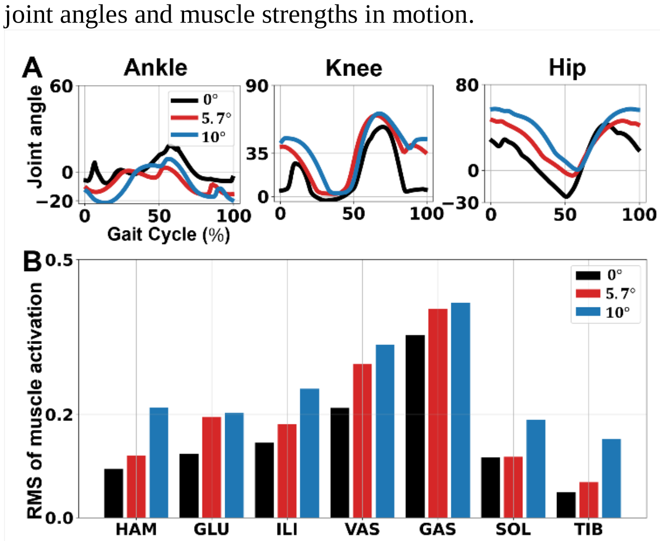

Figure 4. Comparison of (A) joint angles and (B) root mean square of muscle activation at different inclinations.

B. Validating the Walking Gait Performed by Video-derived Musculoskeletal Model

The results of the comparison with the measured data from the subjects are shown in **Fig. 5**. The changes in knee and hip angles acquired from the simulations were generally consistent with the changes in experimentally measured joint angles [18]. This implies that the video-derived musculoskeletal model has a good ability to estimate joint angles in motion. In the case of the ankle joint, compared to the experimental data, there was a significant lack of angular flexion in the ankle joint when simulating walking on a flat ground versus on an incline. This may be due to the miscalculation of the Hertz/Hunt-Crossley sphere at the toe and heel of each foot in the simulation.

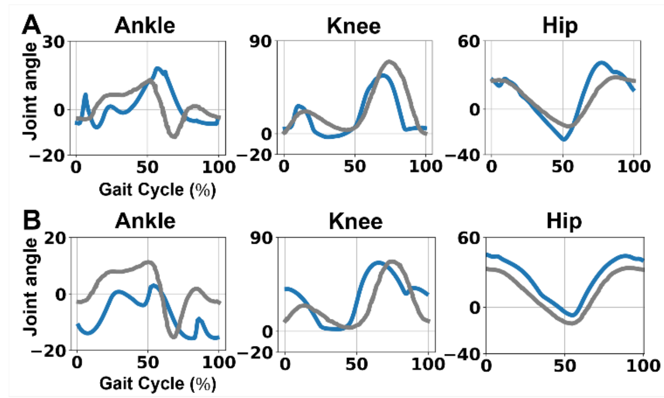

Figure 5. Comparison of joint angle changes between our proposed method (blue line) and gait features [18] (gray line). (A) On the flat ground. (B) On the inclination of 5.7 degrees.

C. Gait Adaptation due to Joint-Assisted Torque

As the knee exoskeleton assisted in climbing by stretching the knee joint, the muscle activation of all the posterior sides of the lower limbs decreases (HAM, GLU, GAS), as shown in **Fig. 6**. In addition, the muscles on the anterior side of the lower limbs did not decrease in muscle activation (ILI, VAS, TIB), which might be due to these muscles pulling the exoskeleton with mass when the lower limbs swing forward. While the ankle muscles were in contact with the ground, the muscles on the posterior side of the ankle had a passive force as the inclination increases, and only the muscles on the posterior side of the ankle had an increased activation.

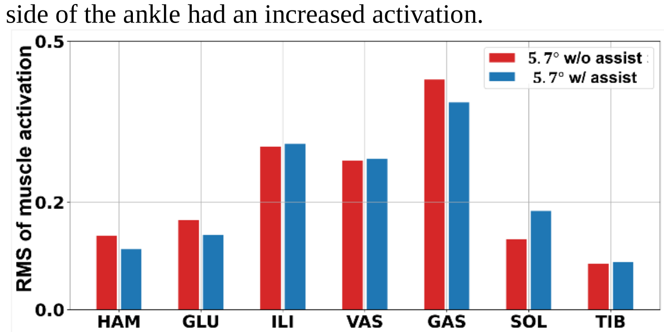

Figure 6. Comparison of muscle activation with (w/) and without (w/o) exoskeleton assistive torque when the ground inclination is 5.7 degrees.

IV. CONCLUSION

We proposed to use a video-derived musculoskeletal model to predict gait adaptation via exoskeletal assistance through predictive simulations. In addition, adding ground inclination and backpack loads to the predictive simulation amplifies and observes the anomalous effects of potential model distortions. Empirical sensitivity analysis demonstrated that the musculoskeletal model derived from the lightweight and affordable mobile phones has kinematic and kinetic reliability and thus has the potential to be applied in clinical practice to predict gait adaptation during exoskeletal assistance. Further deployment to a real exoskeleton and related safety training for the subjects is necessary for our follow-up study.

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