Prediction of Walking Kinematics and Muscle Activities under Idealized Lower Limb Exoskeleton Assistances

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Abstract

This study examines the biomechanical effects of idealized multi-joint exoskeleton assistances on hip, knee, and ankle joints. We conducted predictive simulations of walking without assistance and with seven different assistance cases including assistance to each joint, assistance to any two joints, and assistance to all three joints. A 2D musculoskeletal model with 10 degrees of freedom and 18 muscles was used and the OpenSim Moco optimal control solver was employed for all predictive simulations, which aimed to minimize the weighted sum of several objectives including metabolic cost, muscle activation, joint coordinate acceleration, motion tracking, and whole-body center of mass (COM) acceleration. The results showed that all assistance cases changed the joint kinematics of the walking motion to different degrees and for most cases the exoskeleton assistance reduced muscle effort substantially. By comparing with the unassisted case, we found that the two cases with assistance to all three joints and to the hip-ankle joints both provided more than 50% reduction in metabolic cost of transport (COT), followed by assistance to hip-knee and knee-ankle joints with less than 40% reduction. As for the single joint assistance cases, assistance to the hip joint appeared to be the most effective with around 34% reduction in COT, followed by the assistance to the ankle joint with around 22% reduction, whereas the assistance to the knee joint was much less effective (with less than 10%).

Keywords: Exoskeleton, Musculoskeletal Model, Optimization.

Introduction

Given the importance of walking in the daily activities of human life, researchers in the field of assistive robotics have dedicated substantial effort to develop wearable devices known as exoskeletons to assist human for the applications of human performance augmentation or rehabilitation. As straightforward as it might seem to most of us, walking is a very skillful activity and requires the interplay and coordination of several motor control circuitries in the human brain, spinal reflexes, sensory feedback and muscle activations (Nielsen, 2003). Injecting assistance to such a complex process for the benefit of the wearer is a particularly challenging task. Regardless of several decades of exoskeleton research it was only in 2013 that an exoskeleton was able to achieve metabolic cost savings in walking (i.e., the exoskeleton being able to lower energy expenditure in comparison to the no device baseline). As of 2020 around twelve exoskeletons had recorded net metabolic savings ranging from 3.3 to 19.8% in walking (Sawicki et al., 2020). This holdup can be attributed to the limitations in the intuition based experimental methods with control parameter tuning that were used in the past. In recent years, systematic methods like the human-in-the-loop (HIL) optimization method have enabled faster exploration of optimum assistance parameters and have achieved high metabolic energy savings (Bryan et al., 2021; Ding et al., 2018; Kim et al., 2019; Zhang et al., 2017).

In contrast to the experimental methods, physics-based simulations have the potential of exploring assistive device control parameters more thoroughly with no risk to the subjects. Additionally, all related kinematic, kinetic and muscle mechanics details are readily available at the end of the simulation for analysis. Several studies have used this kind of an approach to study the effects of assistive devices on humans during walking (Grabke et al., 2019) or running (Zhou & Chen, 2020). A human walking with idealized assistive devices while carrying loads was simulated using the CMC (Computed Muscle Control) algorithm available within OpenSim (Dembia et al., 2017). Another simulation utilizing CMC revealed that idealized hip actuators have significantly greater benefit on energy cost saving in the elderly population compared to idealized ankle actuators (Cseke et al., 2022). The CMC method tracks experimental kinematic data with minimal variation in kinematics and cannot handle global objectives that depend on the entirety of the motion (Dembia, 2020).

On the other hand, optimization with the direct single shooting method has been used by some researchers (Geijtenbeek, 2019; Ong et al., 2019; Song & Geyer, 2015; Veerkamp et al., 2021) to overcome some of the limitations inherent to CMC. In our previous work, we employed a single shooting based method to find optimized hip assistance profiles, together with reflex based neural control, during walking (Ratnakumar & Zhou, 2021). Nonetheless, the single shooting method requires numerical integration of the dynamic equations to generate the motion trajectory and hence is computationally expensive (Dorn et al., 2015). In addition to single shooting, direct collocation, a direct optimal control method that relies on gradient-based optimization has been used for musculoskeletal motion tracking and prediction (Falisse et al., 2022; Febrer-Nafría et al., 2022; Nguyen et al., 2019; Park et al., 2022). The introduction of the open-source toolkit, OpenSim Moco (Dembia et al., 2020), has made direct collocation more accessible to the musculoskeletal biomechanics community. In direct collocation, the controls and states are parameterized and the need for explicit integration is eliminated.

In this study, a direct collocation-based optimization method was adapted to co-optimize idealized exoskeleton hip, knee and ankle joint assistance torques in conjunction with the gait and muscle control parameters. The optimization objective includes several terms such as metabolic cost, muscular effort, center of mass acceleration, and tracking of a reference walking motion. Using the tracking term in the objective function and optimizing the gait allows the kinematics to deviate from the tracking data, which enables motion adaptation to exoskeleton assistances. The optimization method was used to solve a case of walking without assistance and seven cases of walking with bi-directional hip, knee, and ankle assistances, for which we compared the changes in kinematics, metabolic cost, and muscle activation.

Methods

The musculoskeletal model used in this study represents an adult with a mass of 62 kg and an approximate height of 1.7 m, which represents a global anthropometric average for mass (Walpole et al., 2012) and a normal mid-range body mass index of 21.5. The model shown in Figure 1 is a modified version of 'gait10dof18musc.osim' available within OpenSim Moco. It is a 2D model and has 10 degrees of freedom (DOFs) (lumbar, bilateral hips, knees, and ankles, and 3 global DOFs) and 9 major muscles per leg: gluteus maximus (GMAX), iliopsoas (IL), hamstrings (HAMS), rectus femoris (RF), vasti (VAS), biceps femoris short head (BFSH), gastrocnemius (GAS), tibialis anterior (TA) and soleus (SOL). This model utilizes the smooth and differentiable DeGrooteFregly muscle model (De Groote et al., 2016), which is suited for gradient-based optimization methods. The lumbar joint was modeled as a pin joint and a coordinate actuator is added to the joint as no muscles span this joint. A modified version of the Hunt Crossley contact model (Serrancolí et al., 2019) was utilized to model smooth contact forces between the ground and the spheres placed at the heels and at the fronts of the feet.

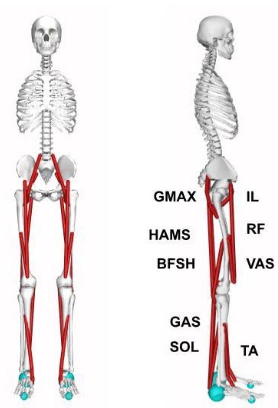

Figure 1. The musculoskeletal model.

Walking without assistance (NoExo) and walking with seven different combinations of bi-directional single- and multi- joint torques were optimized with the OpenSim Moco framework. The term "bi-directional torque" means that the torque can vary in both flexion and extension directions. The following joint assistance cases were realized by adding ideal actuators with bounds between -100 Nm to 100 Nm to the model: HIP – only hip joints are assisted; KNE – only knee joints are assisted; ANK – only ankle joints are assisted; HIP+KNE – hips and knees are assisted; HIP+ANK – hips and ankles are assisted; KNE+ANK – knees and ankles are assisted; ALL – all hips, knees and ankles are assisted.

Optimization of walking with and without assistances was formulated as optimal control problems within Moco. The optimization variables include controls and states (i.e., muscle controls or excitations, joint coordinate angles, and assistance torques as coordinate actuation). The constraints include equations of motion, kinematic constraints (such as symmetry and periodicity), state and control upper and lower bounds, boundary constraints and time limits, etc. A reference walking motion data, originally obtained from predictive simulations representing walking at a speed of 1.32 m/s (Falisse et al., 2019), was used as tracking data and as the initial guess for the NoExo case as well as for the assistance cases except for ALL and HIP+KNE cases, for which the kinematics deviated from the reference motion the most and thus the predicted results from other cases were used instead.

The objective or cost function employed in this study is defined as follows:

$$Total\ Cost\ (J_T) = \int_0^{t_f} \left(w_1 J_{MER} + w_2 J_{COM} + w_3 J_{Joint} + w_4 J_{Control} + w_5 J_{Track}\right) dt \tag{1}$$

The sum of normalized muscle metabolic energy rates (i.e. COT), J_{MER}, is calculated with a smooth approximation of the 2016 Uchida metabolic model (Uchida et al., 2016). The whole-body COM acceleration goal, $J_{COM} = w_x a_x^2 + w_y a_y^2 + w_z a_z^2$ with the weights $[w_x, w_y, w_z] = [30.0\ 2.0\ 0.0]$, penalizes excessive acceleration of the body which helps with reducing the vertical ground reaction during initial contact. The joint acceleration term, $J_{Joint} = \sum_i \ddot{\theta}_i^2$ with θ_i denoting the i-th joint angle, encourages minimal jerk in the lower limb joints. The control term, $J_{Control} = \sum_i w_i\, x_i^2$ with x_i denoting the control signals, includes only the muscle effort by setting the weight w_i for the exoskeleton assistance torques and the lumbar coordinate actuation to zero and all muscle weights to one.

The weights for each cost function term used for the simulations are: $w_1 = 1, w_2 = 0.01, w_3 = 2.5e^{-4}$, $w_4 = 10$ & $w_5 = 10$. The number of mesh intervals was set to 40 and convergence tolerance at $1.0e^{-4}$. All optimizations were run on a personal computer with an Intel Core i7-8550U processor, containing a total of 8 cores, at 1.8 GHz. The simulation time per case varied between 30 minutes and a few hours.

Results

Figure 2 shows the kinematics and vertical GRF for all simulated cases. Experimental human gait data (joint angles and ground reaction forces) at free walking speed reported by Schwartz et.al. (Schwartz et al., 2008) is used for comparison. The hip angles show the closest fit to the experimental data whereas the ankle angles have the largest deviation from the experimental data. The knee angle deviations are higher in the stance phase with relatively small flexion, and the swing phase also exhibits a lower flexion angle compared to the experimental value.

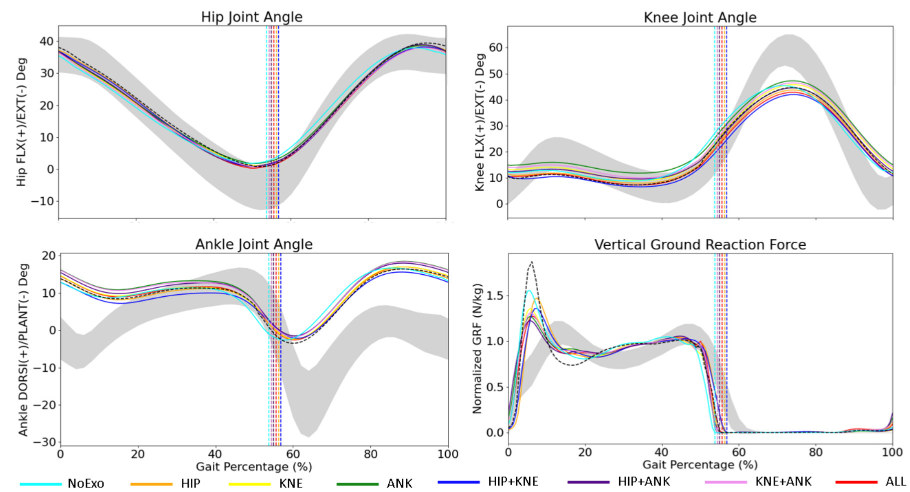

Figure 2. Kinematic and vertical GRF variations for all cases. The vertical lines indicate the stance-swing transition times. The black dash lines are the reference motion data (Falisse et al., 2019) for tracking. The reference data for GRF was not used in the optimization but is included here for comparison. The experimental free speed kinematic/GRF Mean+/-SD data from (Schwartz et al., 2008) is plotted as the gray shaded area.

Muscle activations from the simulations are plotted in Figure 3 and compared with electromyography (EMG) data from Knutson et.al. (Knutson, 1995). As it can be seen from the figure, most of the muscles have similar activation timing or patterns as the experimental data with the exception of the RF muscle. We noticed that there are inconsistencies in reported RF EMG measurements in literature. For example, the RF EMG data from Rajagopal et al. (Rajagopal et al., 2016) has quite different timing and pattern and is closer to our prediction. The VAS muscle exhibits some additional activation during the stance-swing transition in the simulations while the experimental data from Knutson et.al. does not display this behavior. Nonetheless, the data from Rajagopal et al. does show VAS activation during the transition. Our optimization predicted very low activation for the BFSH muscle similar to the study by Falisse et al. (Falisse et al., 2019) and the reasons for this remain to be investigated.

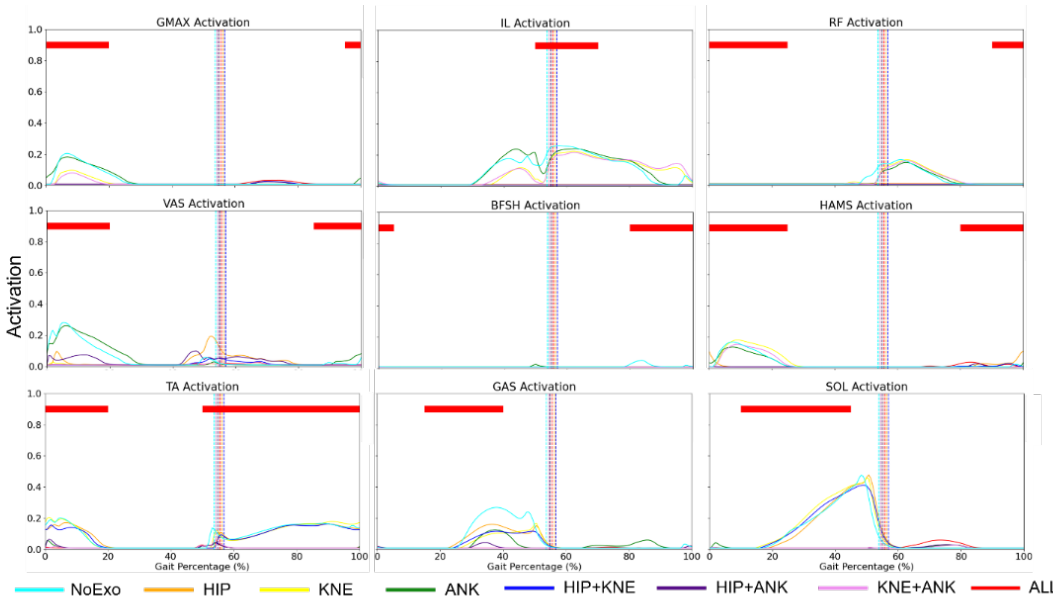

Figure 3. Predicted muscle activations compared to experimental data from (Knutson, 1995). The red horizontal bars indicate when a muscle is active during walking based on (Knutson, 1995).

The changes in COT, defined as the normalized metabolic energy cost by the distance traveled and subject weight, is presented in Figure 4. The baseline NoExo case has a COT of 3.56 J/kg/m which is slightly higher than typical experimental readings that are around 3.35 ± 0.25 J/kg/m (Miller, 2014). The HIP assistance case has the highest reduction in COT amongst the single joint cases with 34% (COT drops to 2.36 J/kg/m), followed by the ANK case with 22% reduction. The KNE assistance case by itself only reduces the COT by 8%. But adding knee assistance to the ankle for the KNE+ANK case seems to be relatively effective (the COT reduction of KNE+ANK is higher than the summation of the ANK case and the KNE case). Adding knee assistance to the HIP+ANK case for the ALL case seems to help very little (an additional 1.5% reduction only).

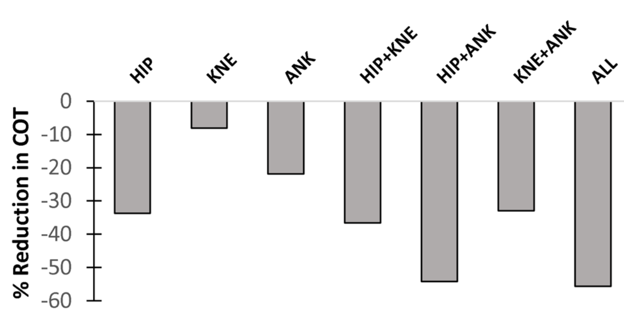

Figure 4. COT reductions in comparison with the NoExo case.

Discussion and Conclusions

This paper presents a direct collocation-based optimization approach to co-optimize idealized exoskeleton assistances with gait (joint motions) and muscle control for walking prediction. Predicted joint coordinate motions and muscle activations of a full gait cycle are compared for all cases including the case without exoskeleton and seven cases of single- or multi- joint assistance. Clearly, we can observe the changes to the gait due to the assistances. The predicted joint motions are close to the reference motion we chose but deviate from the experimental data. Since the reference motion was also predicted with optimization from a 2D model (Falisse et al., 2019), the deviation is explained by Falisse et al. as a result of model choices instead of local optima. Extending the model from 2D to 3D (Falisse et al., 2019) or adding toe degrees of freedom to the foot (Falisse et al., 2022) likely will improve the prediction outcomes. Since in our prediction method, tracking is a part of the objective function, we expect better joint motion prediction if real experimental data is used as the reference motion, which is a planned next step of this study. In terms of the predicted GRFs, we found that the use of a whole-body COM acceleration objective term has a substantial impact on reducing the first peak in the vertical GRF, which is closer to the experimental data. We also noticed slight dragging of the feet (very small GRF during the swing phase) in several cases as shown in Figure 2. This issue may be resolved if we use real experimental data as indicated above. Otherwise, adding an additional term to the objective function to penalize foot dragging during the swing phase can also be considered in the future work.

By comparing with the case without assistance, we observed that most assistance cases reduced the muscle activations and as a result the COT substantially. For single joint assistance, the hip assistance is the most effective in reducing COT, followed by the ankle assistance, whereas the knee assistance is the least effective with only 8% reduction in COT. These results are coherent with the current understanding of the positive work performed by the hip or ankle is much greater than the knee in the total energy expenditure of walking (Sawicki et al., 2009). For the two-joint assistance cases, the HIP+ANK assistance is the most effective, with the reduction in COT being over 50% and very close to the ALL case. Our findings in COT reduction with single- or multi- joint assistances are similar in trend to the results by Bianco et al. (Bianco et al., 2022). However, in their study, the gait kinematics was not co-optimized with the assistances and the unassisted and assisted simulations used the same walking kinematics. In addition, only uni-directional joint assistance was considered in each of their assisted simulations whereas our study considered bi-directional assistance for all cases.

In summary, we believe our modeling study has a great value in exoskeleton actuation design and optimization. Experimental methods such as the HIL optimization (Zhang et al., 2017) are becoming more popular but they still require extensive subject testing and oftentimes the number of control parameters that can be optimized are limited. Our study provides insights on the effects and limits of single- or multi- joint assistance and can help engineers and scientists in prioritizing assistance to certain joints and in providing assistance with optimal timing and assistance profiles.

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