An EMG-marker tracking optimization method to simulate equinus gait

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1 Introduction

Estimating musculo-tendon and joint contact forces in dynamic movement remains a challenge. This preliminary study aims to adapt an EMG-marker tracking optimization method [1,2], *i.e.* a forward dynamics approach, to a musculoskeletal model of the lower limb during gait. To illustrate this method, a dataset of equinus gait has been collected on a healthy participant and applied to a generic musculoskeletal model.

2 Material and methods

2.1 Lower limb musculoskeletal model

A generic three-dimensional musculoskeletal model of the lower limb [3] was used in this study. To simplify the dynamic optimizations in this proof-of-concept, this model was reduced to 5 rigid segments, *i.e.* pelvis and right thigh, patella, shank and foot, and 6 degrees of freedom (DoF), *i.e.* 3 DoFs for the pelvis vs. ground motion and 1 DoF at the hip, knee, and ankle joints. Joints were actuated by the muscle torques resulting from 17 muscle lines of action, and the DoFs of the pelvis vs. ground motion were actuated by 3 generalized forces applied on the pelvis. Twenty-six markers were defined so that the marker locations from the experimentations were reproduced. All model components that depend on distances, segment mass and inertial parameters were scaled using OpenSim 3.3 [4]. The resulting scaled model was transferred to the freely available bioRBD musculoskeletal modelling package (https://github.com/pyomeca/biorbd) based on the Rigid Body Dynamic Library [5].

2.2 Equations of motion and activation dynamics

Generalized accelerations $\ddot{\mathbf{q}}$ of the rigid multibody system were computed using a forward dynamics approach for given generalized joint positions $\mathbf{q}$, joint velocities $\dot{\mathbf{q}}$ and forces $\boldsymbol{\tau}$:

$$\ddot{q} = M(q)^{-1}\left(\tau(q,\dot{q},a,e) + C(q)^T\lambda - N(q,\dot{q})\dot{q} - G(q)\right) \quad (1)$$
$$s.t.\ C(q)\ddot{q} + \dot{C}(q)\dot{q} = 0$$

where M is the inertia matrix, C is the external contact Jacobian matrix, λ is the Lagrange multipliers vector (corresponding to the ground reaction forces R_GRF), N is the nonlinear effects (*i.e.* Coriolis and centrifugal forces) vector, and G is the gravity effects. In line with equinus gait, one contact point was defined at the forefoot and constrained to null velocity and acceleration during the whole contact phase. Musculo-tendon forces were computed from muscle activations a using a Hill-type muscle model with a generic force-length-velocity relation [6]. Muscle activation dynamics was implemented as a set of first-order differential equations as described in [2].

2.3 Dynamic optimizations

Controls, state variables and optimal maximal isometric forces were jointly optimized through an EMG-marker tracking optimization process [1]. This optimization consisted in the minimization of the differences between predicted and measured marker trajectories (M_p and M_m) in the sagittal plane, predicted and measured ground reaction forces (R_p and R_m) in the sagittal plane, and predicted and measured muscle neural excitations (e_p and e_m, only for muscles with EMG records). To predict the activity of muscles for which EMG records were not available, the objective function J consisted in finding the least squared muscle activations a:

$$\boldsymbol{J} = \sum_1^N \left(\boldsymbol{w_M}\|\mathbf{M_p} - \mathbf{M_m}\|^2 + \boldsymbol{w_e}\|\mathbf{e_p} - \mathbf{e_m}\|^2 + \boldsymbol{w_R}\|\mathbf{R_p} - \mathbf{R_m}\|^2\right) + \boldsymbol{w_L}\int_0^T \mathbf{a}(\boldsymbol{t})^2 \boldsymbol{dt} \quad (2)$$

where w_M, w_e, w_R and w_L are weighting factors adjusted to the relative importance of each term, T is the duration of the current stage and N the related number of time frames. This objective function was minimized under boundary constraints applied to state and control variables, null velocity and acceleration of the contact point, and periodicity constraints.

2.4 Simulations

Each dynamic optimization was solved using a direct multiple shooting algorithm with MUSCOD-II [7]. To simulate a step, three stages were defined in this problem, corresponding to the stance phase (*i.e.* with an external contact between foot and ground), the swing phase (*i.e.* without external contact between foot and ground), and the first frame of the next stance phase following the impact between foot and ground (required for the periodicity constraints). These stages were

divided into 25, 25, and 1 intervals, respectively. The initial guess was set to the measurement values for joint positions and velocities, to 1% for activations and excitations and to 0 for the controls corresponding to the generalized forces applied on the pelvis.

2.5 Dataset

All data were recorded on a healthy volunteer (male, 35 years old, 165 cm, 66 kg) with no neuro-orthopedics trouble. This participant gave informed written consent prior to his inclusion. The protocol was conformed to the Declaration of Helsinki and approved by the Institutional Review Board. The 3D trajectories of 26 reflective cutaneous were recorded using an optoelectronic system (OQUS-4, Qualisys AB, Sweden) sampled at 200 Hz. Ground reaction forces and moments were recorded using two force plates (OR6-5, AMTI, USA) sampled at 2000 Hz. The EMG activity of 9 right leg muscles was collected with a wireless electromyographic system (DTS clinic, Noraxon, USA) sampled at 2000 Hz and normalized to the highest EMG magnitude recorded during isometric maximal voluntary contractions. The participant was asked to perform an equinus gait by producing voluntarily controlled co-contractions of the muscles crossing the ankle joint to restrain ankle dorsiflexion. Eight right gait cycles were recorded and analyzed in this study.

2.6 Analysis

To evaluate the capacity of the model to reproduce the measured gait pattern and muscle excitations under the mechanical constraints imposed to the model, goodness-of-fit parameters have been used. Root mean square errors (RMSE) and coefficients of determination (R^2) were computed to assess the differences in intensity and shape, respectively, between measured and estimated excitations, joint angles and ground reaction forces. Furthermore, the coefficient of determination (CC) [8] was computed for these muscles.

3 Results

The convergence time of the 8 optimizations using MUSCOD-II was 232.63 ± 62.34 min on an Intel® Core™ i5-3570 CPU @3.4 GHz. Concerning tracked muscle excitations, the temporal muscle activity of the model is globally close to the measurements with an average CC of 76.79 ± 5.29 %. RMSE values are generally low with an average value of 0.15 ± 0.13 (for adimensioned values between 0 and 1). However, RMSE is higher for gastrocnemius medialis (0.26 ± 0.05) and tibialis anterior (0.43 ± 0.08). The use of a reduced number of muscles could be a cause of this inaccuracy. For all muscles, the correlation remains low with an average R2 at 0.02 ± 0.52. Concerning all other muscles, we generally observe an excitation higher than the one of muscles of the same group for which a tracking of excitation was applied. Concerning pelvis position/orientation and joint angles, the model estimations are close to the measurements. Average RMSE are 0.005 ± 0.005 m for pelvis translations, and 1.92 ± 1.33° for pelvis rotation and joint angles. However, RMSE is higher for the ankle joint (3.97 ± 0.92). For all degrees of freedom, the correlation remains very high with an average R2 at 0.94 ± 0.09. Concerning ground reaction forces (Fig. 1), the model estimations are generally close to the measurements (the average RMSE is 17.28 ± 5.46 N). For both forces, the correlation remains very high with an average R2 at 0.97 ± 0.03.

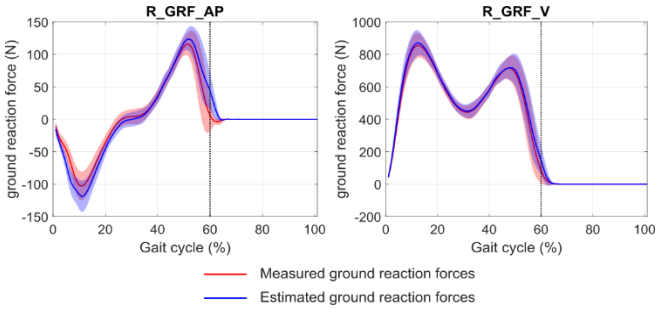

Figure 1: Mean and standard deviation of measured and estimated vertical (R_GRF_V) and anterior/posterior (R_GRF_AP) ground reaction forces during gait cycle.

4 Conclusions

To the best of our knowledge, the use of a direct multiple shooting algorithm in MUSCOD-II on a musculoskeletal model with the tracking of measured marker trajectories, EMG and ground reaction forces has never been performed to date. As already demonstrated by Bélaise et al. [1,2], this approach allows an accurate reproduction of joint kinematics and ensures a good temporal muscle activity in a faster way than traditional forward dynamic approaches. We have also highlighted that the tracking of ground reaction forces was possible and accurate, even without the use of a complex foot/ground contact model. Further simulations on a larger dataset from multiple patients are now needed to support these first results.

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