Trajectory Optimization of a 3D Musculoskeletal Model with Inertial Sensors

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Summary

We propose trajectory optimization for estimation of three-dimensional (3D) kinematics and kinetics of running from inertial data which resulted in high correlations for the sagittal plane and moderate for the frontal and transverse plane.

Introduction

Inertial measurement units (IMUs) consist of accelerometers and gyroscopes and are light weighted and cheap wearable sensors which have the potential to replace lab-based optical motion capturing (OMC). For walking, conventional inverse dynamic methods were used after estimating kinematics and ground reaction forces and moments from inertial data [1]. In contrast to that, we first presented trajectory optimization to directly track noisy inertial data with a planar musculoskeletal model for walking and running [2]. Trajectory optimization ensures a dynamically consistent simulation. However, the planar lower-body model used in [2] is not capable of capturing for example lateral stability required to evaluate running shoes. Here, the trajectory optimization driven by IMU data is extended towards the estimation of 3D kinematics and kinetics of running.

Methods

A 3D musculoskeletal model with 33 degrees of freedom and 92 Hill-based muscle tendon units [3] was used to track inertial data of seven IMUs at the lower body in a trajectory optimization. Sensor signals were simulated by placing virtual sensors on the model. Gyroscope signals were obtained from the skew-symmetric matrix $[\boldsymbol{\omega}]_\times = \boldsymbol{R}^T \dot{\boldsymbol{R}}$, where $\boldsymbol{R}$ describes the global orientation of the segment and $\dot{\boldsymbol{R}}$ its time derivative. Accelerations $\boldsymbol{a}$ were computed as follows:

$$\boldsymbol{a} = \boldsymbol{R}^T (\ddot{\boldsymbol{r}}_{Seg} + \ddot{\boldsymbol{R}}\, \boldsymbol{p}_{Sen} - \boldsymbol{g}),$$

where $\ddot{\boldsymbol{r}}_{Seg}$ denotes the global acceleration of the segment, $\boldsymbol{p}_{Sen}$ denotes the sensor position in the segment coordinate system, and $\boldsymbol{g}$ denotes the global gravity vector.

The state $\boldsymbol{x}(t)$ and control $\boldsymbol{u}(t)$ trajectories of a gait cycle were simulated by minimizing a combination of tracking error, cubic neural excitation, torque controls actuating the arms, and a small regularization term. The tracking error of the 42 sensor axes was expressed as squared difference between the virtual signal and the mean measured signal normalized to the measured variance. The trajectory optimization was constrained to be periodic and by the model dynamics which were formulated implicitly as $\boldsymbol{f}(\boldsymbol{x}, \dot{\boldsymbol{x}}, \boldsymbol{u}) = \boldsymbol{0}$ [3]. The simulation was solved by 100-node direct collocation using Backward Euler and IPOPT.

The approach was evaluated using running at three different speeds of nine subjects with OMC as reference [2]. Coefficients of multiple correlation (CMCs) [4] were computed between IMC and OMC for joint angles and joint moments of the hip, knee, ankle, subtalar and mtp joint and for ground reaction forces. Finally, CMCs were averaged over running speeds and subjects using Fisher's z-transform.

Results and Discussion

The simulation tracked the measured IMU data well and rejected soft tissue artifacts. Sagittal plane kinematics and kinetics showed excellent (CMC: 0.93-0.98) and strong (CMC: 0.81-0.92) correlations, respectively (see Figure 1). However, correlations were weak for joint angles and moments of the subtalar and mtp joint.

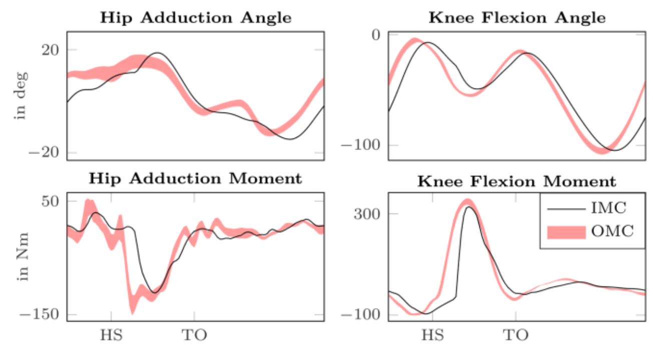

Figure 1: Comparison of inertial motion capturing (IMC) and optical motion capturing (OMC) for running of one subject.

Similar correlations have been reported for sagittal plane kinematics and kinetics [1,2] whereas frontal and transverse plane variables appear to be harder to estimate [1]. Variables of the subtalar and mtp joint are sensitive to the ground contact model which could be further improved. Trajectory optimization results in consistency between kinematics and kinetics in contrast to inverse dynamics [1] or machine learning. Simulation quality for motions with directional changes, like curved running, will be further evaluated.

Conclusions

We have shown that the full state and muscular control of a 3D musculoskeletal model can be estimated by tracking inertial data with trajectory optimization. The results agreed well with optical motion capturing for the sagittal plane and moderately for the frontal and transverse plane.

Acknowledgments

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