Combined Deep learning and Top-Down Optimization for Estimation of Kinematics from IMUs

Soyong Shin[1]*, Eric Rapp[1], Reed Ferber[2] and Eni Halilaj[1]
[1]Department of Mechanical Engineering, Carnegie Mellon University, Pittsburgh, PA, USA
[2]Faculty of Kinesiology, University of Calgary, Calgary, Alberta, Canada
Email: soyongs@andrew.cmu.edu

Introduction

One limitation to measuring human movement patterns from inertial measurement units (IMUs) is the susceptibility of magnetometer readings to ferromagnetic interferences. To address this limitation, we recently proposed the use of deep neural networks to predict joint angles directly from inertial data, without relying on noisy magnetometer readings [1]. To further improve the accuracy and generalizability of these models, here we introduce a new framework that combines deep learning with top-down optimization.

Methods

To train the deep neural networks, we used treadmill running data from 586 subjects and walking data from 384 subjects collected at the University of Calgary using an optical motion tracking system. Synthetic IMU data (linear acceleration and angular velocity) were generated by placing virtual IMUs on the segment marker clusters. Sensor noise was modelled synthetically by adding Gausian noise [1], while sensor placement variability was modelled using data augmentation techniques [2]. As a baseline, we built deep neural networks to predict the joint angles, $\boldsymbol{\alpha_i}$ ($\boldsymbol{i} \in \{\mathbf{1}, \mathbf{2}, \mathbf{3}\}$), and orientations of the adjacent segment sensors, $\boldsymbol{q^S} = \{\boldsymbol{q^{S1}}, \boldsymbol{q^{S2}}\}$, from the inertial data.

We then implemented a top-down optimization algorithm, which updated the orientation of each adjacent segment until the discrepancy between the inertial data associated with these predicted orientations and the "true" inertial data from the virtual senors was minimized. The result of the optimization (β_i) was defined as the angle between two optimized sensor orientations. To derive final angle prediction (θ_i), we used weighted average of two prediction results α_i and β_i, where $\theta_i = w_i\alpha_i + (1 - w_i)\beta_i$. We set terminal stance of the predicted angle as zero and express the subsequent predictions as a function of the angle at that pose. We call this process passive pseudo calibration, since it does not require user engagement but is effective in reducing prediction error in subjects with atypical limb alignments.

Results and Discussion

Walking kinematics could be predicted with a mean (± STD) RMSE of less than 2.95° (± 0.82°), while running kinematics could be predicted with a mean RMSE of less than 3.24° (± 1.12°). During walking, flexion/extension was the most accurate degree of freedom, with a mean RMSE of less than 1.07° (± 0.37°) across the ankle, knee, and hip joints, followed by ab/adduction with a mean RMSE of less than 1.98 (± 0.97) and internal/external rotation with a mean RMSE of less than 2.95° (± 0.82°). Similarly, during running, flexion/extension was the most accurate degree of freedom, with a mean RMSE of less than 1.29° (± 0.40°) across the ankle, knee, and hip joints, followed by ab/adduction with a mean RMSE of less than 2.33° (± 0.84°), and internal/external rotation with a mean RMSE of less than 3.24° (± 1.12°). The higher RMSE in internal/external rotation may be explained by the lack of magnetometer data, which, when undisturbed, contribute toward heading estimation. Further, optical motion tracking, which was used as ground truth here, exhibited similar accuracies across degrees of freedom.

Optimization improved prediction of knee flexion by over 15%, hip flexion by over 10%, and ankle flexion by over 15%. When passive pseudo-calibration was applied, optimization had an even larger effect on final kinematics. In this case, prediction of knee flexion improved by over 45%, hip flexion by over 60%, and ankle flexion by over 40%, compared to the neural network outputs. Using this pseudo-calibration framework the predictive accuracy of the algorithms can be tuned passively after a few gait cycles, without requiring attention from the user. Also, because we trained the models on augmented data, sensor placement errors did not significantly degrade the predictive accuracy of the overall framework. While validation with true sensor data is a necessary follow-up step, the accuracy of the presented framework is a promising advance toward prediction of joint kinematics from wearable sensors without relying on ferromagnetic interference, drift-prone algorithms, and/or error-prone calibration techniques.

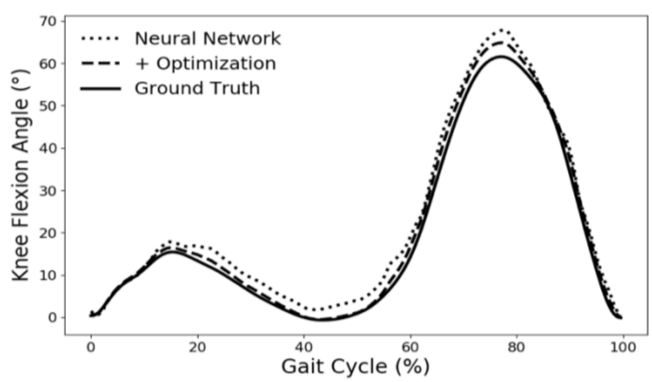

Figure 1: Knee flexion over a representative gait cycle for a test subjet computed from marker data (solid), predicted from a deep neural network (dash), and adjusted with top-down optimization (dotted), demonstrating how optimization improves joint angle estimation.

Significance

Wearable sensors offer a promising alternative for motion analysis in natural environments by overcoming some of the limitations of traditional marker-based techniques: spatial limitation, expensive equipment, and need for human expertise. The hybrid deep learning and top-down optimization approach presented here brings us a step closer toward accurate estimation of kinematics from IMUs. Progress in this direction should enable large-scale studies and new insights into disease progression, patient recovery, and sports biomechanics.

References

1. Thomsen W., Ferber R., Halilaj E.. "Deep neural networks for estimating knee joint kinematics from inertial measurement units." ISB 2019, Calgary, Canada.
2. Thomsen W., Ferber R., Halilaj E. "Predicting Joint Kinematics from Sensors with Varying Body-Segment Alignments." CMBBE 2019, New York, NY