Estimating Biological Hip Torque During Overground Ambulation: A Machine Learning Approach

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Introduction

As gait biomechanics research continues to progress, it is important to quantify biological hip torque in unstructured environments, such as those outside of the lab. Wearable sensors provide an opportunity to compute joint dynamics without the need for external sensing. Linked-segment model-based approaches require sensors distal to the joint of interest, such as pressure insoles, which are subject to low resolution GRF measurements and often result in cumbersome, multi-joint sensor suites[1,2]. Machine learning (ML) methods can compute biological joint torque without direct measurement of GRFs by leveraging the limited domain of joint torques during ambulation[3,4]; however, generalizability of these methods to changing ambulation modes remains unknown. Thus, we conducted our study, hypothesizing that hip torque RMSE and peak magnitude and timing error estimated by a neural network (NN) are less than those resulting from an average curve of each ambulation mode.

Methods

Five able-bodied male subjects completed the IRB approved experimental protocol by ambulating over 0°, ±7.8°, ±9.2°, and ±12.4° slopes while wearing a bilateral robotic hip exoskeleton. The hip exoskeleton was used to collect hip encoder and 6-axis thigh-mounted intertial measurement unit (IMU) data during ambulation. Data was transformed into the ML model feature space by computing the mean, standard deviation, and most recent value over a 350 ms sliding time window for each exoskeleton sensor channel. Biological hip torque was computed using the Inverse Dynamics Tool in OpenSim with motion capture and force plate data collected during each trial[5]. A 4 layer NN with 30 nodes per hidden layer was trained using the exoskeleton feature data, labelled by the corresponding hip torque values (Fig. 1A). Additionally, the baseline method was fit as the average hip torque curves for the level ground (LG), ramp ascent (RA), and ramp descent (RD) conditions. The two methods were evaluated using three criteria compared to the ground truth hip torque values: 1) estimation RMSE; 2) peak magnitude error, computed as the absolute difference between the peak estimated and ground truth values; and 3) peak timing error, computed as the absolute difference in gait phase during peak estimated and ground truth values. A paired t-test ($\alpha = 0.05$) was used to compare the NN and baseline methods for each criteria.

Results and Discussion

The estimated hip torque of the NN and baseline methods are shown for an example step during RA in Fig. 1C. On average, the NN model reduced hip torque RMSE, peak magnitude error, and peak timing error by 29.7±12.2%, 32.6±17.4%, and 12.8±13.9% compared to the baseline method, respectively ($p=0.015$, $p=0.057$, $p=0.117$) (Fig. 1B). Thus, the NN model more accurately estimated the shape and magnitude of varying ambulation modes compared to the baseline method as expected; however, both the NN and baseline methods accurately estimated peak torque timing to within 2% of the gait cycle due to the low variability in this metric among ambulation modes. Thus, the NN model is a useful approach for estimating biological joint torques when the estimate must be sensitive to shape and magnitude of the curve, such as in gait analysis and exoskeleton control.

Significance

This study validated an ML algorithm for estimating biological hip torque using only mechanical sensors during various ambulation modes. We demonstrated the benefit of using this model compared to the baseline method of average values due to its improved accuracy and reduced requirement of user state information, such as ambulation mode. Thus, our study provides a promising method for estimating biological joint torque for applications including out-of-lab experiments and exoskeleton control while varying ambulation modes.

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References

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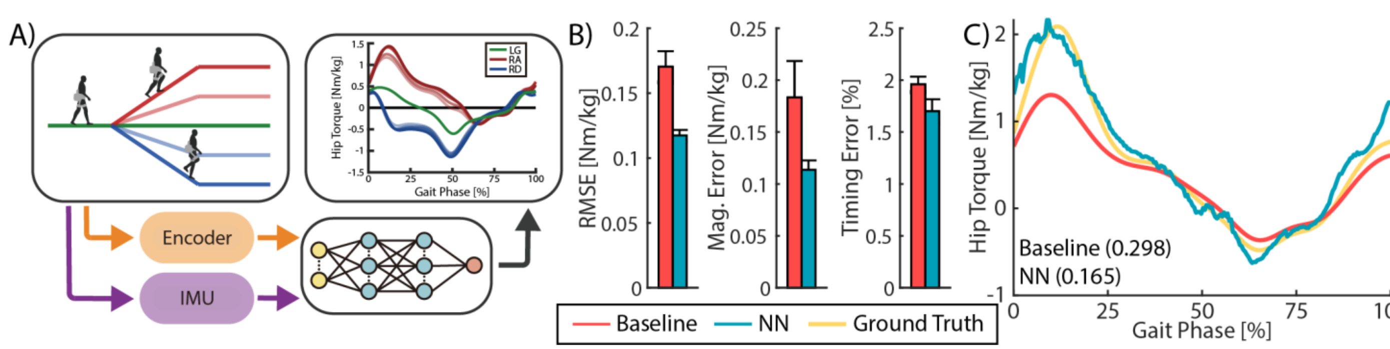

Figure 1: A) A diagram of the neural network based torque estimater is shown. Mechanical sensor data is input to a neural network after windowing and feature extraction. B) Average estimated torque RMSE, peak magnitude error, and peak timing error among ambulation modes is shown for the NN and baseline method. C) Estimated and ground truth hip torque is shown for a single step during the 12.4° incline (RMSE in parentheses).