Real-time hip biomechanics from physics-informed neural networks and wearable sensors

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Summary

We developed and validated a physics-informed neural network (PINN) that estimated hip angles, moments, muscle forces, and hip contact forces (HCF) from inertial measurement units (IMU) and electromyography (EMG). The PINN used data from 3 IMU and 4 EMG to estimate physically and physiologically bound hip biomechanics. The PINN was trained with data from an EMG-informed neuromusculoskeletal model and evaluated *via* leave-one-subject-out and leave-one-task-out cross validation. The PINN accurately estimated hip angles, moments, muscle forces, and HCF, and can operate in real-time when paired with a smart garment.

Introduction

Movement retraining has been proposed for the management of musculoskeletal conditions like osteoarthritis. Key drivers of tissue adaptation (i.e., internal biomechanics: forces, stresses, and strains) are altered by movement retraining [1], and might be optimized by targeted interventions. However, the time-consuming and technically challenging nature of estimating tissue biomechanics prevents implementation of movement retraining and out-of-lab monitoring of subsequent effects. Artificial neural networks can estimate internal biomechanics from sparse data [2], but accurate real-time estimation has not been achieved using wearable systems. The aim of this study was to develop and validate a PINN for real-time prediction of hip biomechanics (angles, moments, muscle forces, and HCF) that can be paired with a smart garment for management of hip osteoarthritis.

Methods

Three-dimensional optical motion capture, ground reaction forces, 9-axis IMU, and EMG from 14 lower-limb muscles were recorded synchronously from 17 healthy participants (aged 18-35 years) during 6 tasks: treadmill walk (level, incline, decline), treadmill run (level, incline), bilateral squat, split squat, counter-movement jump, and forward jump. A validated neuromusculoskeletal modelling (NMS) pipeline using OpenSim and calibrated EMG-informed [3] modelling estimated lower-limb joint angles, moments, muscle forces, and HCF. The PINN was developed in TensorFlow (v2.6) and trained to estimate hip angles, hip moments, hip muscle forces, and HCF from 3 IMU (pelvis and both thighs) and 4 EMG (single leg gluteus maximus, gluteus medius, vastus lateralis, and biceps femoris). The PINN combined long short-term memory networks with a previously validated feed-forward NN to solve muscle-tendon unit kinematics [4]. The PINN generated muscle excitations for 25 hip-spanning muscles and calculated muscle forces using known muscle contractile mechanics. The HCF was the vector sum of muscle and intersegmental forces. Loss penalties were added to ensure consistency between predicted moments and muscle forces, smooth physiologically plausible predictions, and reduce total muscle excitation. The PINN predictions were compared to neuromusculoskeletal models using root-mean-square-error (RMSE) within a leave-one-subject-out and leave-one-task-out cross-validation (CV). The trained PINN was tested for real-time capability using data streamed from a custom smart garment (Griffith University).

Results and Discussion

For leave-one-subject-out CV, the PINN well predicted sagittal plane hip kinematics (RMSE=3-6°), hip moments (RMSE=0.15-0.31 Nm/kg), and peak HCF (RMSE=9-12% of peak) across all tasks (Figure 1). Leave-one-task-out CV predictions suggest limited generalizability to tasks with little similarity to training data. When paired with a smart garment, computational delay was <40ms on an Intel i9-12900K CPU.

Conclusions

The developed PINN predicted hip biomechanics relevant to cartilage health with low error compared to gold standard NMS models, and demonstrated real-time prediction when combined with an easy-to-use smart garment. The developed PINN will enable novel movement retraining interventions for people with hip osteoarthritis.

References

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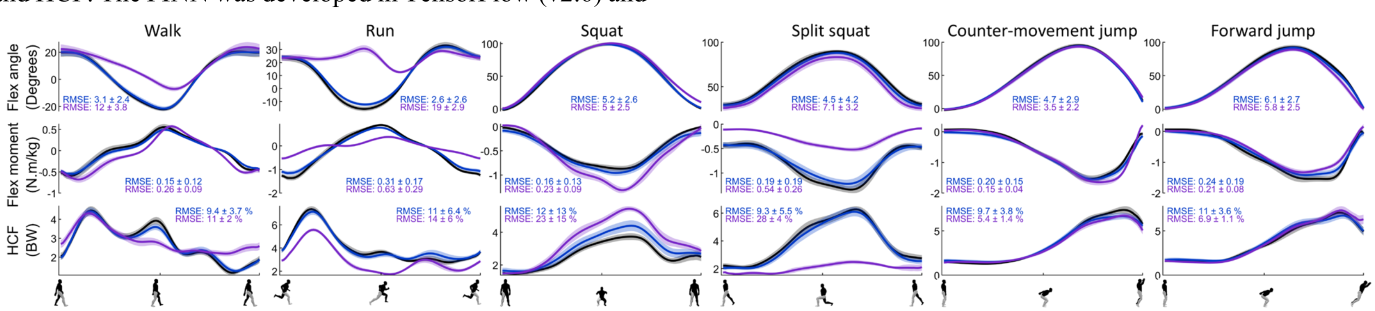

Figure 1. Ensemble average (±1 standard error) of hip flexion angle (top), hip flexion moment (middle), and hip contact force magnitude (bottom) generated by the PINN using LSO (blue) and LTO (purple) compared to NMS (black).