Estimating Knee Joint Angles During Cycling Using Deep Learning and Wearable Sensors

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Summary

In this study, a long short-term memory (LSTM) neural network was trained using inertial measurement unit (IMU) data to predict knee joint angles during cycling. Even with a small dataset, results produced are similar to other methodologies which require a calibration stage and expensive motion capture. Further training on a larger dataset could produce better predictions and reduce model overfitting.

Introduction

Cycling is a professional sport, a form of transport, a physical activity undertaken by millions worldwide, and is often used in rehabilitation for neurological and orthopaedic conditions [1, 2]. To optimise cycling performance and minimise injury risk, an understanding of the relevant biomechanics is required. One such element is the cyclist's changing knee joint angles, however, gathering this information is often not easy or accessible due to the requirements of lab sessions with expensive apparatus. There are few studies in the context of cycling employing machine learning models which, given the impact signal processing has had on wearable technology in sports and clinical biomechanics, is a lacuna. Furthermore, existing methods require extensive calibration procedures [3]. Hence, we investigated whether a simple neural network could be trained to estimate knee joint angles using only IMUs, eliminating the need for calibration.

Methods

Six participants (2 female) were fitted with 39 reflective lower body markers and a 16 camera Qualisys system captured marker positions at 150 Hz. For our comparison, 8 Delsys IMUs attached to the left and right vastus lateralis, semimembranosus, gluteus maximus and medial gastrocnemius muscles collected data at 1350 Hz. Participants performed nine 2-minute cycling trials in which cycling cadence and target power were varied (60, 80, 100 rpm and 60, 80, 100 Watts) using a Wahoo Kickr bicycle at a self-selected saddle height. The marker data for each participant's trials were first filtered using a low-pass filter with a cut off frequency of 6Hz. The marker data were then used to segment the corresponding IMU data into 'pedal cycles' with each cycle consisting of a full rotation of the right foot. Each cycle was then time-normalised to 101 datapoints. OpenSim models were scaled for each participant and paired with the collected marker data to perform inverse kinematics. This process provided gold standard joint angles that were then used to train and test a deep learning model. The deep learning model was made up of a bilateral LSTM layer followed by 2 dense layers. Leave one subject out (LOSO) validation was used to evaluate model performance on each participant's data. Model accuracy was evaluated by calculating the root mean square error (RMSE) between the gold standard knee angle values and those output from the model. The method used for pre-processing of the data and network design was adapted from existing literature using an LSTM architecture [4].

Results and Discussion

Our neural network was able to achieve performance metrics comparable to existing methods predicting knee joint angles [5] and markerless motion capture [6], while using only IMU accelerometer and gyroscope data and without participant-specific calibration. Results showed the network achieved an RMSE, across all participants, of 6.1 degrees (Table 1). In the best performing case, the model achieved an RMSE of 2.9 degrees.

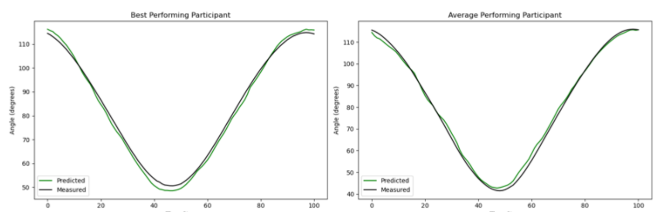

Figure 1: Best predicted pedal cycle for the best and average performing participant during LOSO validation

Fluctuations in the model's performance, however, can be observed (Table 1), with a contributing factor being the limited dataset. Hence, the model likely struggled to estimate angles for participants with more outlying characteristics and correspondingly differing input signals.

Conclusions

We demonstrated that deep learning has the potential to be used to accurately estimate knee angles, with an average RMSE of 6.1 being achieved. We suggest that with additional training on a larger dataset the model would achieve better generalization and thus obtain better results from a simple and relatively inexpensive and accessible approach.

References

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Table 1: RMSE Validation loss for each subject during LOSO validation

Validation Participant	**P1**	**P2**	**P3**	**P4**	**P5**	**P6**
Mean RMSE (°)	5.0	8.6	3.3	6.3	2.9	10.3