Tracking Bilateral Lower Limb Kinematics of Distance Runners on Treadmill Using a Single Inertial Measurement Unit

Yuvraj Patra, Qi Liu, Rosa H. M. Chan, Daniel Thomson, Daniel H.K. Chow, Ben Fuller, Roy T.H. Cheung

Abstract— **Distance running related injuries are common, and many ailments have been associated with faulty posture. Conventional measurement of running kinematics requires sophisticated motion capture system in laboratory. In this study, we developed a wearable solution to accurately predict lower limb running kinematics using a single inertial measurement unit placed on the left lower leg. The running data collected from participants was used to train a model using long short-term memory (LSTM) neural networks with an inter-subject approach that predicted lower limb kinematics with an average accuracy of 80.2%, 85.8%, and 69.4% for sagittal hip, knee and ankle joint angles respectively for the ipsilateral limb. A comparable accuracy range was observed for the contralateral limb. The average RMSE (root mean squared error) of sagittal hip, knee and ankle were 8.76º, 13.13º, and 9.67º respectively for the ipsilateral limb. Analysis of contralateral limb kinematics was performed. The model established in this study can be used as a monitoring device to track essential running kinematics in natural running environments. Besides, the wearable solution can be an integral part of a real-time gait retraining biofeedback system for injury prevention and rehabilitation.**

I. Introduction

Distance running is a popular form of exercise but running related injuries are very common. Up to 79% of regular runners incur an injury annually, and these injuries may be related to faulty running kinematics. For example, patellofemoral pain, a common musculoskeletal condition in distance runners, has been associated with excessive hip adduction, overstride (i.e., knee hyperextension upon landing) and a rearfoot strike pattern [1]. Analysis of lower limb kinematics can be useful for injury prevention and rehabilitation by identifying faulty running kinematics and gait retraining, which has been reported to be an effective method to correct running biomechanics and improve symptoms related to running [2]. Traditionally, measurement of running kinematics requires motion capture (MoCap) system, which is expensive and impractical to use in outdoor environment. With the recent advancements in sensor technology, inertial measurement units (IMUs) have become viable tools for gait analysis in natural running environments.

Previous studies have used IMU sensors to develop various machine learning models to study distance running. A model proposed in one of these studies can classify performance levels of runners and concurrent prediction of biomechanical parameters using convolutional neural network (CNN) and multilayer perceptron (MLP) model architectures [3]. In another study, data from three IMU sensors were used to train an artificial neural network (ANN) that could predict knee kinematics and vertical ground reaction force (GRF) [4]. CNN model trained on acceleration data from five IMUs has been used to estimate anteroposterior and vertical GRFs [5]. To enhance user friendliness, recent studies attempted to minimize the number of IMU. For example, the feasibility of ipsilateral limb prediction has been demonstrated with an LSTM model for multi-joint angle estimation with a single IMU sensor (i.e., two sensors are required for bilateral limb kinematics tracking) [6]. There are a few studies that have proposed models capable of predicting lower limb kinematics for the contralateral limb (cross-leg kinematics) with an acceptable accuracy and minimal error. For instance, cross-leg kinematics estimation with a CNN model using an IMU placed on the right tibia, exhibited an accuracy ranging from 78.4% to 93.6% [7].

In the present study, we aim to develop a solution to predict lower limb running kinematics using a single IMU placed on the left lower leg (inferior to the tibial tuberosity) with a deep learning model based on LSTM architecture for both ipsilateral and contralateral limbs.

II. Methodology

A. Participants

19 healthy recreational runners (ten male and ten female participants; age: 30.4 ± 7.1 years; height: 1.74 ± 0.10 m; weight: 77.5kg ± 16.0 kg) were recruited in this study. Participants were recreational runners with a weekly mileage greater than 12 km. Those who had reported any running related injury in the past 6 months or had any previous lower limb surgeries were excluded. The experimental procedures were reviewed and approved by the Human Research Ethics Committee, Western Sydney University (Reference number: H14164). Each participant provided written consent prior to the tests [8].

B. Instrumentations

One OPAL sensor (APDM Wearable Technologies Inc., Portland, United States of America) was placed at the inferior to the tibial tuberosity of the participants. Using this sensor, data was captured, including acceleration and anatomical angles of the lower limb, at a sampling rate of 128 Hz. The sensor contained an accelerometer with a measurement range of ± 16 g, a gyroscope with a measuring range of ± 2,000 degree/s and a magnetometer with a measuring range of ± 0.0008 Tesla. The data collected by the accelerometer and the

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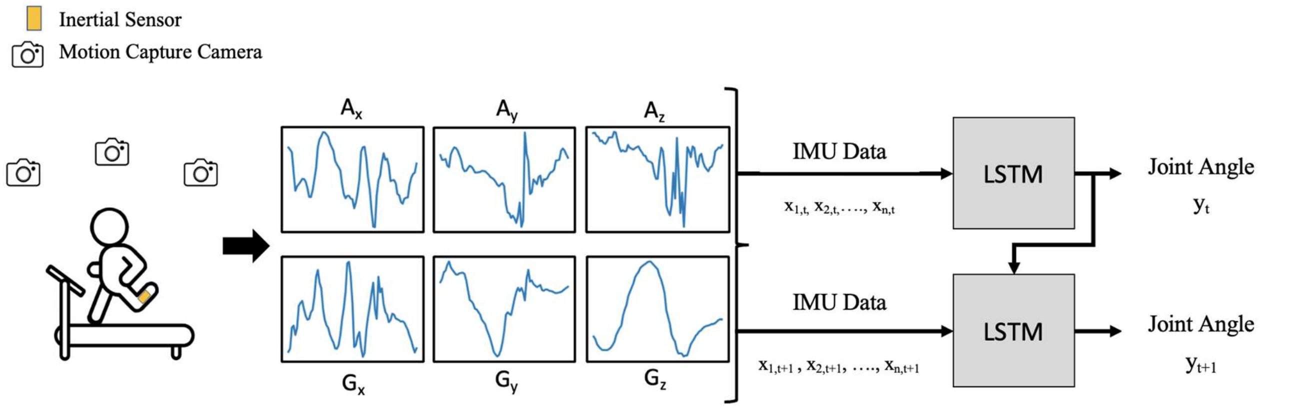

Figure 1 Schematic diagram of the experimental setup showing data collected from IMU sensor processed by LSTM Model for joint angle prediction. 6 input features (acceleration (x, y, z) and gyroscope (x, y, z)) are used for joint angle prediction. The notation x_t and y_t denotes the preprocessed IMU input data and joint angle prediction output at time t respectively. The figure shows how output at time t affects the result at time t+1 since it is used as an input to the LSTM in the subsequent step.

gyroscope were further used for data processing. Additionally, a markerless MoCap system (Vicon, Oxford, United Kingdom; Theia Markerless, Ontario, Canada) was used in this study. The system contained 8 video cameras sampling at 100 Hz. It has been reported to be a reliable and valid method to accurately measure similar gait kinematics in comparison to marker-based motion capture methods i.e., current gold-standard [9]. For this study, the focus was to estimate the lower limb kinematics using a single IMU positioned on the left lower leg (inferior to the tibial tuberosity)(optimal placement position as per previous studies) [10] and compare them against measurements made by the MoCap system to evaluate our predictions.

C. Experimental procedures

Prior to running on the treadmill, participants completed a short warm-up which included two sets of 10 repetitions of standing calf raises, air squats, forwards and sideway leg swings. Each of them then went through a static calibration process by standing still for 5 seconds, and the foot placement was standardized using an APDM plastic marker on the motionless treadmill. This became a point of reference for the static posture of the participants. The participants started the treadmill, accelerated to a set speed, and ran at that speed for a duration of 30 seconds before stopping. They repeated this process twice at 4 different speeds of 9, 10, 11 and 12 km per hour, with the order of the speeds being random. To maximize the variability of data, participants data was collected from both MoCap and IMU at each speed, resulting in eight separately recorded blocks having static, accelerating, and known speed data for each participant [8].

D. Data Processing

There were 6 types of data used from the data collected by the IMU sensor. These include data collected for each coordinate axis (x, y and z) for the accelerometer and the gyroscope. The data collected by the MoCap sensor (30 seconds of running data before stopping) was resampled from 100 Hz to 128 Hz (higher frequency of IMU sensor) using interpolation, to match the size of the data collected by the IMU. This helped create consistent and well-mapped datasets. Data collected from all the participants at all speeds was aggregated and saved in distinct repositories to allow each joint plane angle to be trained individually with the proposed deep learning model.

E. Deep Learning Model

The IMU sensor collects timeseries data which is sequential in nature. This study proposes a deep learning model using LSTM (Long short-term memory) neural networks (a type of RNN), owing to its ability of remembering long-term dependencies [11]. The proposed model consists of an input layer (for 6 IMU input features), 1 hidden LSTM layer (using tanh activation function), followed by 1 hidden Dense layer and finally, 1 output Dense layer (both with a linear activation). It uses mean squared error (MSE) metric as the loss function and the standard Adam optimizer for model compilation. Min-Max normalization method was applied to the input features to improve training, ensure faster convergence of the model, and prevent the model from overfitting. The IMU data was normalized and used as input features for the model to make predictions of the joint angles for ipsilateral and contralateral lower limbs. As shown in Figure 1, the joint angle output at time *t* was used for predicting the output at time *t+1,* in addition to the normalized IMU input features entering the LSTM at time *t+1*.

TABLE I. RMSE, NRMSE, AND R-SQUARED VALUES OF EACH JOINT ANGLE FROM INTER-SUBJECT ANALYSIS

Joint Angle	*Ipsilateral limb*			*Contralateral limb*		
	RMSE(°)	*NRMSE(%)*	*R-squared*	*RMSE(°)*	*NRMSE(%)*	*R-squared*
Sagittal Hip	8.76	12.53	0.802	8.75	15.60	0.805
Sagittal Knee	13.13	12.35	0.858	18.14	18.97	0.704
Sagittal Ankle	9.67	16.12	0.694	9.21	23.01	0.663

F. Model Evaluation

This study used root mean squared error (RMSE), normalized root mean squared error (NRMSE), and R-squared (R^2), to quantitatively measure and compare the prediction of joint angles for ipsilateral and contralateral lower limbs. RMSE quantifies the error and R-squared measures the goodness of fit in the prediction of lower limb kinematics. For inter-subject analysis, the model was trained separately for each joint angle plane using the preprocessed datasets. Data were split into 80% training and 20% testing, and the training data were further split into 80% training and 20% validation for 5-fold cross-validation (model fitted 5 times). Subjects were separately selected for training and testing. Hyperparameter optimization was performed using Grid Search 5-fold (k-fold) cross-validation method and scored using the root mean squared error to identify the optimal hyperparameters for the model. The hyperparameters tuned included the number of neurons in each layer (units), the learning rate of the model, and the dropout.

The hyperparameters and their respective search spaces were as follows:

- Units: [32, 64, 128]
- Learning Rate: [0.0001, 0.00001, 0.000001]
- Dropout: [0.0, 0.1, 0.2]

Besides these model hyperparameters, different lengths of sequence history (or timesteps) of IMU data were tested to check the effect on model performance during cross-validation. The range of timesteps tested was 16 to 64 timesteps in steps of 16. Since all the data was resampled to 128 Hz, this translated into a time sequence history ranging from 125 milliseconds to 500 milliseconds in steps of 125 milliseconds (4 possible values). The optimal model hyperparameters and the optimal sequence history length were identified and used to evaluate the model on the testing dataset for each joint angle plane. This method of model evaluation helped reduce bias and make the model robust.

III. RESULTS

Using data from the IMU sensor at left lower leg, the LSTM model was able to predict lower limb kinematics for both ipsilateral and contralateral limbs. The joint angles predicted by the proposed model were compared against the ground truth kinematics obtained from the MoCap system.

This study focusses on the prediction of sagittal plane kinematics for hip, knee, and ankle joints. Although attempts were made to predict frontal and transverse plane kinematics, the placement of the left lower leg was insufficient since the model did not yield convincing results. For the sagittal plane kinematics prediction, 30-second running data was taken before stopping across all 4 speeds from all subjects for each joint angle plane and a 5-fold Grid Search cross-validation method of evaluation was adopted. Optimal model hyperparameters and sequence length were identified for each joint angle plane. The best estimator was then used to make predictions on the testing data, and the evaluation metrics were calculated and tabulated in Table 1. As shown Table 1, the average RMSE values of sagittal hip, knee and ankle were 8.76°, 13.13°, and 9.67° respectively for the ipsilateral limb and 8.75°, 18.14°, and 9.21° respectively for the contralateral limb.

IV. DISCUSSION

Injuries related to faulty running kinematics can have detrimental effects on the health and ability of runners. They are evidence to why the study of running kinematics is of importance. This study aimed at predicting lower limb kinematics bilaterally using data from a single IMU sensor placed on the left lower leg. This was achieved using an LSTM model. The model was able to make predictions of sagittal joint angles with an average accuracy of 80.2%, 85.8%, and 69.4% for hip, knee and ankle joints respectively for the ipsilateral limb, with a similar range of accuracy for the contralateral limb. Comparable models have achieved a similar accuracy [6][7]; however, this study was a novel attempt at predicting lower limb kinematics of both ipsilateral and contralateral limbs (bilateral) with a single IMU sensor.

Major biomechanical difference between novice and experienced runners is focused on kinetics (e.g., joint moment), rather than kinematics parameters, which is supported by both cross-sectional [12] and longitudinal studies [13]. Therefore, our solution can be translated to track running kinematics in untrained users. However, there are distinctive running kinematic features among elite runners [14], which is a possible limitation to our solution. Since there is an association between running kinematics and age [15], the model may not be generalized for older runners either. Therefore, in future studies, a larger participant group with a wider variety of demographic features needs to be recruited for the study.

With the help of our model, lower limb kinematics can be monitored by running coaches in real-time, prevent injuries by monitoring the joint angles and make sure that runners do not exceed specified thresholds that can lead to injuries, through gait retraining. This study could help develop a biofeedback device that can alert runners in real-time during infield training and become an essential technology for modifying an athlete's biomechanics.

V. Conclusion

This study proposed a novel method of bilateral lower limb kinematics prediction with an LSTM model using a single IMU sensor data from the left lower leg, with an average accuracy of 80.2%, 85.8%, and 69.4% for sagittal hip, knee and ankle joint angles respectively for the ipsilateral limb, and a similar accuracy range for the contralateral limb. The average RMSE values of hip, knee and ankle were 8.76º, 13.13º, and 9.67º respectively for the ipsilateral limb, and 8.75º, 18.14º, and 9.21º respectively for the contralateral limb. These results show that the proposed model can predict lower limb kinematics bilaterally. Therefore, this model can be employed as a monitoring device to track essential running kinematics in natural running environments and even become an integral part of real-time gait retraining biofeedback system for injury prevention and rehabilitation.

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