A LSTM FRAMEWORK FOR ANKLE JOINT BIOMECHANICS PREDICTIONS FROM INERTIAL SENSORS DURING GAIT

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Introduction

The ankle joint plays a crucial role during gait, articulating the lower limb and foot-ground contact, keeping the body balanced, and transmitting the center of gravity. Evaluating the biomechanics of the ankle joint helps with gait function assessment, pathological gait analysis, and prosthesis and robot design. However, traditional data collection is limited to strict experimental settings and laboratory setups. With the advent of wearable technologies, inertial sensors have appeared as a reliable alternative due to their convenience, low cost, and data collection capability outside the laboratory [1]. This study aimed to implement recurrent neural networks (long-short term memory, LSTM) for predicting ankle joint angle, torque, and contact forces from the inertial sensors.

Methods

Twenty-five healthy participants were recruited for this study following ethical approval, with means and standard deviations of age 25.84±1.18 yrs, height 172.8±5.37 cm, and mass 71.4 ± 8.37 kg, respectively. Two inertial measurement unit (IMU) sensors were attached to the foot dorsum and the vertical axis of the distal anteromedial tibia in the right lower limb to record acceleration and angular velocity during running (Figure 1). Data processing was performed following a protocol established previously [2]. Inverse kinematics (IK), inverse dynamics (ID), and static optimization (SO) were performed to calculate ankle and subtalar joint angle and torque in the sagittal plane and contact forces. The architecture of our LSTM-MLP (multilayer perceptron) model was two layers of bidirectional LSTM with 256 neurons, followed by a three-layer MLP with 256 neurons for the first layer and 512 neurons for the second and third layers. The model was validated and tested in a custom nested K-fold cross-validation process.

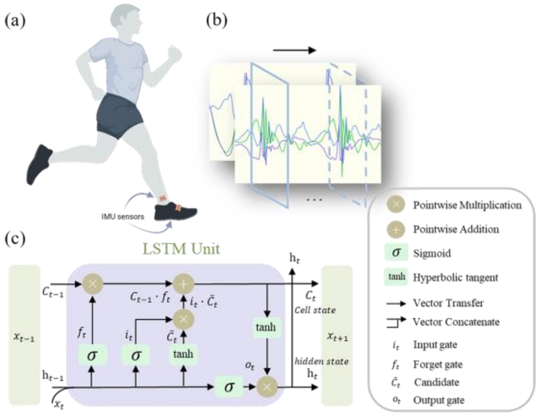

Figure 1: (a) IMU sensor placements; (b) input data; (c) illustration of a single LSTM unit.

Results

The average values of coefficient of determination (R2), mean absolute error (MAE), and mean squared error (MSE) for ankle dorsiflexion joint and moment, subtalar inversion joint and moment, and ankle joint contact forces were 0.89±0.04, 0.75±1.04, and 2.96±4.96 for walking and 0.87±0.07, 0.88±1.26, and 4.10±7.17 for running.

	Walking	Running
Ankle dorsiflexion angle	2.97 ± 0.47	3.21 ± 0.74
Subtalar inversion angle	3.34 ± 0.47	4.15 ± 0.70
Ankle dorsiflexion moment	0.14 ± 0.02	0.17 ± 0.02
Subtalar inversion moment	0.05 ± 0.01	0.04 ± 0.01
Anterior/posterior reaction force	0.27 ± 0.07	0.33 ± 0.05
Vertical reaction force	0.52 ± 0.09	0.43 ± 0.03
Medical/lateral reaction force	0.10 ± 0.01	0.11 ± 0.01

Table 1: Root mean squared error (RMSE) between measured values from the motion capture system and predicted values from the LSTM model for walking and running from nested k-fold cross-validation (mean± std).

Discussion

Deep learning algorithms integrating with inertial sensors have emerged in recent years, as they are convenient and can capture biomechanics data outside the traditional gait laboratory. In this study, we found LSTM could predict ankle joint, moment, and contact forces with strong correlations (R2 > 0.8) and acceptable error during walking and running. Furthermore, nested K-fold cross-validation guaranteed good generalization by the multiple-validation, testing, and training models in a subject-independent manner [3].

This study proposed an LSTM framework for predicting the ankle joint, torque, and joint contact force from IMU sensors. It is a valuable tool for evaluating ankle biomechanics in lower limb pathological diagnosis and rehabilitation that is not limited to the experimental setting and is cost-effective.

References

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