An Ensemble Machine Learning Approach for the Estimation of Lower Extremity Kinematics Using Shoe-Mounted IMU Sensors

Md Sanzid Bin Hossain[1], Joseph Dranetz[1], Hwan Choi[1], and Zhishan Guo[1]
[1] University of Central Florida, Orlando, FL, USA
[1]E-mail: {hwan.choi, zsguo}@ ucf.edu

INTRODUCTION

Evaluating human body movement is an essential step for biomechanical analysis and assessing a disease's condition and progression. The infrared light motion capture system is a standard method for assessing joint kinematics. However, the motion capture system requires a specific setup in a confined area, leading to challenges with quantitative assessment of walking conditions found in daily living. Using multiple inertial measurement units (IMU) sensors allows for the evaluation of movement outside the lab. Still, they are too burdensome for daily living due to needing sensors in specific locations on each limb. There is a need for an accurate kinematics assessment with a reduced number of sensors---this paper focuses on the setting where only one sensor is mounted on each shoe. Machine learning has been used to estimate joint kinematics with a reduced number of IMU sensors [1], but the resultant joint angle errors are not minor enough for applying movement evaluation. This paper proposes a new machine learning algorithm that provides highly accurate and real-time hip, knee, and ankle joint angle estimations in the sagittal plane using two shoe-mounted IMU sensors. We adapted five deep learning networks by implementing various configurations of Convolutional Neural Networks (CNNs) or Long-Short Term Memory (LSTM) Networks and ensembled them all together to leverage the advantage of each model. Our ensemble technique provides high correlation between predicted joint kinematics and kinematics measured with an infrared light motion capture system.

CLINICAL SIGNIFICANCE

Optimal control of wearable devices requires the input of different gait-related parameters. Our algorithm helps produce kinematics using a small number of sensors, which can be used to control patients' devices.

METHODS

Nine healthy subjects (six male and three female) participated in the study. The Institutional Review Board (IRB) of the University of Central Florida (UCF) approved the study protocol. We placed two IMU sensors on the participants' shoes. The participants walked on the treadmill at four different speeds: slow, normal, fast, and very fast, for approximately 2 minutes per setting. We set up four different non-dimensional walking speeds; slow, normal, fast, and very fast from their leg length [2]. Then, the participants walked on the treadmill for 2 minutes in each speed setting. Thirty-six reflective markers were placed on the participant based on a modified Helen-Hayes marker set [3]. Three-dimensional marker trajectories were captured with twelve infrared light cameras at a sampling rate of 100 Hz. The accelerometer and gyroscope data were recorded with a sampling frequency of ~148 Hz. We used OpenSim [4], an open-source musculoskeletal analysis tool to calculate joint angles during the walking conditions. Our study considers the hip, knee, and ankle angle on the sagittal plane for both legs, which results in six joint angle coordinates. The performance of multiple neural networks may not be the same for a specific dataset. There are variances in the prediction due to the different structure of those networks. Ensembling different neural networks can be used to take advantage of better performing networks. In our work, we take the prediction average of five deep learning models. Our proposed ensemble network outperforms all the neural networks individually. We have used two metrics to evaluate the performance of the model. The Root Mean Square Error (RMSE) and the Pearson correlation coefficient were calculated between the ground truth kinematics and the deep learning model's prediction.

DEMONSTRATION

From the result shown in Table 1, our proposed ensemble technique outperforms all single networks. RMSE of hip flexion angle has decreased 2-10% and 4-8% on average for the right and left leg, respectively. For knee angle, the RMSE reduction is 7-10%, 6-12% for right and left leg. For ankle angle, RMSE improvement is 3-11%, 1-12% for left and right leg, respectively. The correlation was slightly improved for the ensemble method in all joint angles for both left and right leg.

Model	Right			Left		
	Hip	Knee	Ankle	Hip	Knee	Ankle
Conv2D-net	4.01 (0.982)	4.18 (0.985)	2.94 (0.945)	3.86 (0.982)	4.33 (0.984)	2.80 (0.952)
Bi LSTM-net	4.15 (0.981)	4.16 (0.985)	3.09 (0.939)	3.91 (0.982)	4.17 (0.984)	3.10 (0.948)
Hybrid Conv1D-LSTM-net	4.35 (0.981)	4.24 (0.985)	3.20 (0.938)	3.81 (0.984)	4.13 (0.985)	3.13 (0.947)
Hybrid Conv2D-LSTM-net-1	4.15 (0.981)	4.12 (0.986)	3.03 (0.942)	3.80 (0.984)	4.09 (0.985)	2.92 (0.952)
Hybrid Conv2D-LSTM-net-2	4.28 (0.980)	4.10 (0.986)	3.01 (0.944)	3.75 (0.984)	4.02 (0.985)	2.89 (0.951)
Ensemble (Proposed)	**3.94 (0.984)**	**3.83 (0.988)**	**2.86 (0.950)**	**3.60 (0.985)**	**3.80 (0.987)**	**2.77 (0.957)**

Table 1: RMSE (Correlation) of different models for joint angles

SUMMARY

We presented a machine learning technique to estimate lower extremity joint angles in treadmill walking in this work. Previous work estimated the joint angle directly from IMU sensors on each leg segment. This method is less practical as it requires many sensors on the body. Machine learning can be used to map data from a reduced number of sensors with joint angles. In our method, two IMU sensors are fixed on the shoes. As a result, our method can more readily be applied to monitor gait outside of the lab and in daily living conditions.

REFERENCES

1. Gholami, M. et al. (2020) Sensors (Basel), 20(10):2939.
2. Liu, M. Q. et al. (2008) Journal of Biomechanics, 41(15):3243-52.
3. Kadaba, M. P. et al. (1990) Journal of Orthopaedic Research, 8(3): 383-92.
4. Delp, S. L. et al. (2007) IEEE Transactions on Biomedical Engineering, 54(11): 1940-50.

DISCLOSURE STATEMENT. The authors have no conflicts of interest to disclose.