Predicting Kinematics from High-Density Plantar Pressure Sensing

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I. Introduction

Humans naturally distribute pressure across their feet to move efficiently across diverse terrains. Sensory feedback from plantar pressure plays a crucial role in maintaining balance, adjusting posture, and optimizing movement [1]. This feedback allows for fine motor control, enabling dynamic adaptations to varying surface conditions, inclines, and perturbations [1]. Likewise, robots could benefit from high-resolution plantar pressure sensing to enhance stability and adaptability, particularly in unstructured environments. However, despite its importance, there is a significant lack of high-quality datasets linking plantar pressure with joint kinematics, especially in real-world conditions such as uneven or deformable terrain. Understanding this relationship could enable predictive models for human biomechanics and inform robotic locomotion strategies.

Previous studies have attempted to correlate plantar pressure with human motion kinematics, but they face several limitations. Many rely on sparse, low-resolution pressure sensors that fail to capture fine-grained pressure distributions [2-3]. Others estimate joint kinematics indirectly using external motion capture systems, imus, or force plates in controlled lab settings, which do not fully reflect natural locomotion [4-6]. These limitations hinder the development of robotic systems that can leverage plantar pressure sensing for real-time locomotion adaptation.

To address this gap, we developed a high-density (HD) plantar pressure sensor with 1024 sensing elements, enabling precise spatial and temporal resolution of foot-ground interactions. Using this sensor, we can collect an extensive dataset of human locomotion, including walking and running at different speeds on various surfaces. We can then train a predictive model capable of estimating joint kinematics directly from plantar pressure measurements with high accuracy. As a proof of concept, we trained a Gaussian mixture model on plantar pressure data and joint flexion angles from a human walking at three different speeds and accurately estimated the joint flexion angles to within an error of about 1° for each joint.

This work lays the foundation for using plantar pressure sensing not only as a biomechanical research tool but also as a key modality for robotic control. Our next step is to apply this methodology to robotic locomotion, training models that enable robots to dynamically distribute pressure across their feet to optimize balance and movement efficiency. By integrating high-resolution pressure sensing with adaptive control strategies, we aim to develop robots capable of navigating complex terrain with human-like agility, ultimately improving their safety and versatility in real-world applications.

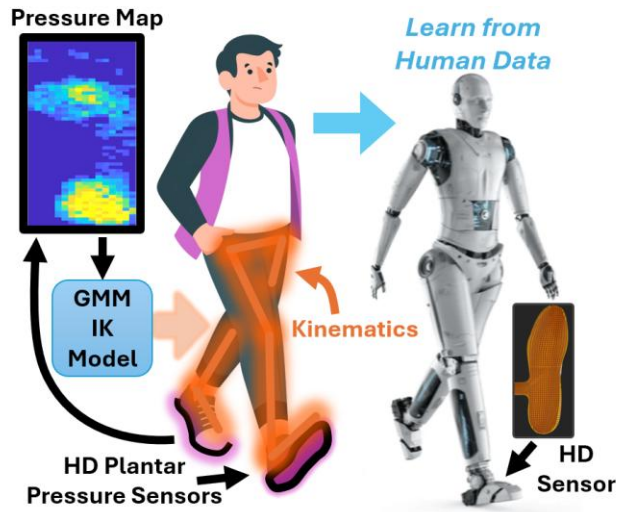

Figure 1. Overview of how plantar pressure data can be used to estimate human kinematics and inform humanoid robotic locomotion.

II. Method

We built a HD sensor using two fPCBs that sandwiched a piezoresistive fabric (Velostat). The top fPCB had of 64 rows of copper traces and the bottom fPCB had 16 columns of copper traces. Each intersection of a column and row formed a tactile sensing element, or taxel, which meant our sensor was made up of 1024 taxels. The sensor readout was implemented using a conventional zero-potential resistive sensor array readout circuit [7]. The measurement of the sensor was done using an ESP32 microcontroller which, along with the measurement circuit, was powered by a 500 mAh LiPo battery and sampled the sensor at 40 Hz. The sensor was cushioned with adhesive foam (NATGAI Sponge Neuprene with Adhesive Foam Rubber Sheet) applied above and below the sensor to create the insole, protecting it from repetitive impact. The insole was placed inside a shoe with the readout board attached to the side with a 3D printed box for testing

To train and test our model, we had four subjects walk on an instrumented treadmill with a VICON motion capture system while wearing a shoe with our sensor at 3 different speeds (0.75 m/s, 1.0 m/s, and 1.5 m/s) for 2 minutes each. The subjects had IR reflective markers placed throughout their body to track the position of their body, and the joint flexion angles were computed using the VICON Nexus Software [6].

*Research supported by a TEDCO MII Grant

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The plantar pressure data from the sensor was processed by first segmenting out individual strides. A stride was defined as starting from a heel strike on one foot and ending at the next heel strike on the same foot. The heel strikes were identified using a threshold of 10% of the range of the average pressure value of the whole sensor. The points that crossed the threshold with a positive slope were heel strikes and those with negative slopes represented toe-offs. The toe-off points were used to separate the stance and swing phases of the gait. Only the data during the stance phase of each stride was used in our kinematic estimation.

For each stance phase, the following features were extracted: peak pressure (PP) coordinate, center of pressure (COP) coordinate, contact area (CA), and pressure-time-integral (PTI). The PP coordinate is the coordinate of the sensing element with the highest amplitude. If multiple sensing elements have the same peak value, then the average position of those elements is taken as the PP coordinate. The COP coordinate is the weighted average of the positions of all sensing elements with an amplitude greater than 0 weighted by the amplitude of each element. The CA is the number of sensing elements with an amplitude greater than 0. The PTI is the area under the curve of the average pressure of the sensor over time.

Gaussian mixture regression (GMR) was used to estimate the joint flexion angles of the hip, knee, and ankle using the features extracted from the sensors. A Gaussian mixture model (GMM) was created to model the joint probability density of joint flexion angles and sensor features as a mixture of normal distributions. Once the model has been fitted, the joint angles for a given pressure profile can be estimated using the conditional probability distribution of the joint angles given the features from the sensor [8]. The number of distributions, or components, used to create the model was selected by calculating the Bayesian information criterion (BIC) for a GMM created using 1 to 20 components. The BIC evaluates a model's likelihood and includes a penalty for increasing the number of parameters to minimize overfitting and improve model efficiency [8]. The number of components that produced the lowest BIC was selected as the best number of components for our model. Our model was implemented in MATLAB using its the fitgmdist function from the Statistics and Machine Learning Toolbox to calculate the BIC for different numbers of components. Once the best number of components was selected, the GMM-GMR package by Sylvain Calinon [9] was used to train and test the GMR. K-fold cross validation with 4 folds and root mean square error (RMSE) were used to evaluate the performance of the GMR.

III. Results and Discussion

Figure 2A shows the average joint flexion angles from Subject 1 for the hip, knee, and ankle across all three speeds. The average angle of the hip ranged from -7.0° to 24.4°, the angle of the knee ranged from 5.5° to 23.8°, and the angle of the ankle ranged from -3.3° to 12.0°. This was the same for the measured and estimated joint angles. The average profiles of the hip, knee, and ankle are consistent with that of a normal gait. The shaded areas show the full range of measured and estimated joint angles. The wide range of angles was due to the different walking speeds. As the walking speeds increase, the angle of the joints in the leg change to produce more force in order to push the human body forward at a faster rate [10]. This results in different joint angle profiles for different walking speeds and different pressure profiles measured by our sensor.

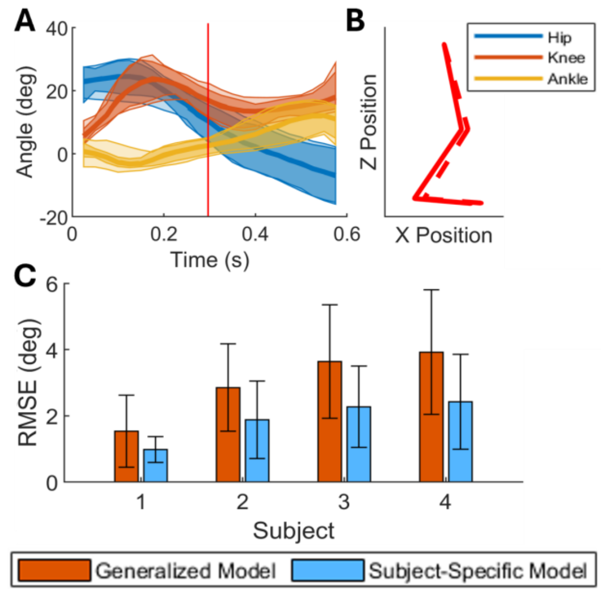

Figure 3. Joint angle reconstruction results. A) Measured and estimated joint angles across all speeds. The solid lines are the average measured joint angles and the dashed lines (not visible due to overlap of solid lines) are the estimated joint angles. The lighter shaded areas are the range of measured joint angles, and the darker shaded areas are the range of estimated joint angles. The red line is the time point at which the measured and reconstructed legs are plotted in B. B) An example of a measured leg (solid line) 0.3 seconds into a step and a reconstructed leg (dashed line) from the estimated joint angles at the same time step. C) The average RMSE for a generalized and subject-specific model for each subject.

The average RMSE for the generalized model trained on all subjects was 3.0° ± 1.5°, with Subject 1 having the least error at 1.5° ± 1.0° (Figure 2C). A subject-specific model reduced the error by 37%, leading Subject 1 to have an error of 0.97° ± 0.39°. An example of the measured position of the leg from Subject 1 at 0.3 seconds into a step and the reconstructed position of the leg based on the estimated joint angles is shown in Figure 2B. While the reconstructed leg is close to the position of the measured leg, the slight offset shows that the small error in angle estimation can compound when reconstructing the position of the leg. Our results show that the GMR model was able to accurately estimate the joint flexion angles from the pressure data captured by our insole when the foot is in contact with the ground. It also demonstrates a strong correlation between plantar pressure and lower limb movement. However, slight differences between individual walking patterns can lead to increased prediction errors with a generalized model. This demonstrates that there is still room for improvement in our angle estimation model. Possible future directions include the use of neural networks such as CNNs, LSTMs, or Transformers.

References

[1] F. J. F. Viseux, “The sensory role of the sole of the foot: Review and update on clinical perspectives,” Neurophysiologie Clinique, vol. 50, no. 1, pp. 55–68, Feb. 2020

[2] Ren, J.; Wang, A.; Li, H.; Yue, X.; Meng, L. A Transformer-Based Neural Network for Gait Prediction in Lower Limb Exoskeleton Robots Using Plantar Force. Sensors 2023, 23, 6547.

[3] Choffin, Z.; Jeong, N.; Callihan, M.; Sazonov, E.; Jeong, S. Lower Body Joint Angle Prediction Using Machine Learning and Applied Biomechanical Inverse Dynamics. *Sensors* **2023**, *23*, 228.

[4] Matikainen-Tervola, E. et al. Validity of IMU sensors for assessing features of walking in laboratory and outdoor environments among older adults. Gait & Posture 114, 277–283 (2024).

[5] Goldfarb, N., Lewis, A., Tacescu, A. & Fischer, G. S. Open source vicon toolkit for motion capture and gait analysis. Computer Methods and Programs in Biomedicine 212, 106414 (2021).

[6] Vicon. Product Model: Vicon Motion Capture System. https://www.vicon.com/hardware/cameras/

[7] R. Yarahmadi, A. Safarpour, R. Lotfi, An Improved-Accuracy Approach for Readout of Large-Array Resistive Sensors. IEEE Sensors J. 16, 210–215 (2016)

[8] Celeste McFarlane, Garima Raheja, Carl Malings, Emmanuel K. E. Appoh, Allison Felix Hughes, and Daniel M. Westervelt. Application of Gaussian Mixture Regression for the Correction of Low Cost PM2.5 Monitoring Data in Accra, Ghana. ACS Earth and Space Chemistry 2021 5 (9), 2268-2279

[9] Sylvain Calinon (2025). Gaussian Mixture Model (GMM) - Gaussian Mixture Regression (GMR) (https://www.mathworks.com/matlabcentral/fileexchange/19630-gaussian-mixture-model-gmm-gaussian-mixture-regression-gmr), MATLAB Central File Exchange.

[10] Fukuchi CA, Fukuchi RK, Duarte M. Effects of walking speed on gait biomechanics in healthy participants: a systematic review and meta-analysis. Syst Rev. 2019 Jun 27;8(1):153.