A Magnetic Field-based Foot Sensor for Legged Robots

Sanhanat Lertvittayavivat[1,†], Dhamdhawach Horsuwan[2,†], Rujikorn Charakorn[2],
Worasuchad Haomachai[2], Poramate Manoonpong[2,3*]
[1]Prince of Songkla University, Songkhla, Thailand
[2]Vidyasirimedhi Institute of Science & Technology, Rayong, Thailand
[3]University of Southern Denmark, Odense, Denmark
[†]These authors contributed equally to this work. *poramate.m@vistec.ac.th

1 Introduction

Foot sensors are essential for legged robots to interact with the environment, and ground reaction force (GRF) measurement is a widely used method for evaluating their dynamics. Traditional 3D force sensors rely on load cells with strain gauges, which are implemented using either three perpendicular sensors [1] or a monolithic structure [2]. While these rigid sensors provide linear responses with minimal impact on positioning, they are challenging to integrate into small-scale robots and cost-effective sensors. Therefore, we propose a novel foot sensor that utilizes a magnetic field with the rubber O-ring as a compliant element to measure a 3D ground reaction force-like profile, providing a cost-effective solution for foot-ground interaction sensing. We validate the reliability of the sensor design through quantitative analysis of the collected data. Finally, we train a convolutional neural networks (CNN) model and demonstrate that it can robustly predict the inclination of an unseen slope given a short time series of sensor readings.

2 Materials and Methods

2.1 Magnetic Field-based Foot Sensor Design

We develop a foot sensor based on a 3D Hall-effect magnetic field sensor (TLV493D-A1B6) housed within a compact sensor frame to measure deformations along three axes. A small embedded neodymium magnet, suspended using a double O-ring configuration, serves as the sensing probe (see Fig. 1). This design allows flexible movement along the z-axis (upward-downward), x-axis (left-right) and y-axis (forward-backward), enabling the sensor to capture force-induced deformations in three dimensions (3D) while maintaining compliance and structural integrity. The coordinate system of the sensor and a cross-sectional view of the sensor are illustrated in Fig. 1.

The sensor housing and sensing probe are fabricated using Fused Deposition Modeling (FDM) 3D printing with PolyLite PLA Pro material from Polymaker, ensuring a lightweight structure with high durability. The sensor ICs are mounted on printed circuit boards (PCBs) alongside an on-board microcontroller, which is responsible for reading sensor data and facilitating communication via the Dynamixel Protocol. This setup enables seamless integration with the robot's control system by using the existing RS-485 bus with Dynamixel Protocol 2.0. To enhance reliability and ease of fabrication, the sensor incorporates commercially available O-rings and a neodymium magnet. The standardized O-rings provide consistent and durable compliance, simplifying the fabrication process compared to silicone molding while maintaining controlled compliance in the sensing mechanism.

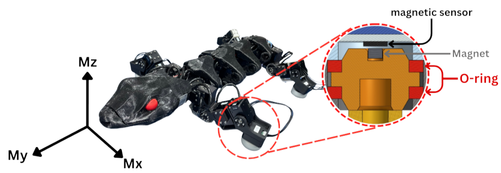

Figure 1: Robotic platform with a cross-sectional view of the magnetic sensor, O-ring, and magnet for ground reaction magnetic field detection.

2.2 Collecting Foot Sensor Data for Predicting the Robot's Climbing Slope Angle

The foot sensors are installed on the foot tips of a four-legged, gecko-like robot [3], which are covered with Dragon Skin 30 silicone rubber. The climbing experiment is conducted on three different slope angles from 0, 10, and 20 degrees. During the experiment, the magnetic field data are continuously recorded from all four feet to capture the foot-ground interaction dynamics. The magnetic field values (M), measured in milliTesla (mT), are recorded at a sampling rate of 18 Hz. The data consist of three components: M_x along the x-axis, M_y along the y-axis, and M_z along the z-axis, representing the magnetic field in three dimensions. To ensure comprehensive data coverage, each test includes the performance of multiple walking steps for all three slope angles. The recorded data are then segmented into individual walking cycles, enabling quantitative analysis of foot-ground interactions and sensor responses across different inclinations (see Fig. 2).

Furthermore, the collected time series magnetic field data are processed and used to train a machine learning model. The goal is to predict the walking inclination angle based on a time series snapshot of sensor readings. We preprocess the data by applying normalization to obtain the zero mean and unit variance. Then, we use the sliding win-

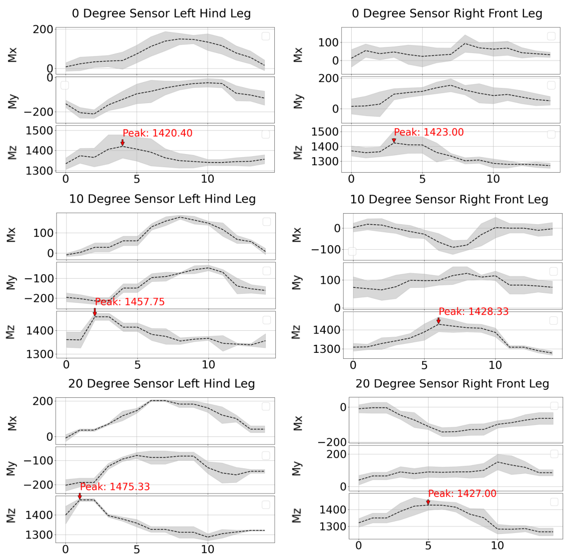

Figure 2: Magnetic field variations (M_x, M_y, and M_z) for left hind and right front leg sensors at 0, 10, and 20 degree. Peak M_z values are marked in red.

dow technique to generate samples. Each sample has a window size of 50 timesteps with 30 timesteps overlapping between windows from the same walking trial. We use five walking trials to generate the dataset. Then, we train a regression model based on CNNs [4] to evaluate the ability to distinguish between different slope angles. We use data from trials with 0, 10, and 20 degrees for training, while data from 5 and 15 degrees are used for testing the generalization of the model.

3 Experiment and Results

3.1 Magnetic Field Profile Analysis

In this study, the magnetic field data of the left hind leg (LH) and right front leg (RF) are selected for analysis at slope angles of 0, 10, and 20 degrees (Fig. 2). Throughout the robot's walking cycle, M_z changed due to foot-ground interaction along the vertical axis, while M_x and M_y changed in response to forces along the lateral and longitudinal axes, respectively. The magnetic field profile analysis is presented in Fig. 2. As the slope angle increased, the peak value of M_z in the LH also increased. More specifically, the peak value was 1420.40 mT at 0 degrees, increasing to 1457.75 mT at 10 degrees and further to 1475.33 mT at 20 degrees. However, the M_z value in the RF showed no significant difference across the three slope angles. This indicates that the robot's hind leg exerts greater effort when climbing steeper slopes, consistent with the GRF analysis from a previous study on a climbing robot [3].

3.2 Predicting the Slope Angle from Foot Sensor Data

To further validate the usefulness of the sensor, we test whether a correlation exists between the sensor profile and the steepness of the terrain using machine learning techniques. First, we visualize the data collected under all inclination levels using t-SNE [5] in Fig. 3 (top). As can be observed, the data collected from different steepness an-

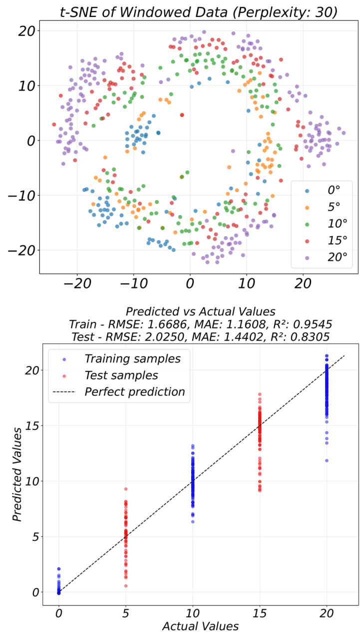

Figure 3: (**Top**) The t-SNE visualization of processed data. Colors represent inclinations under which the data are collected. Data collected from varying inclinations have different distributions and are largely non-overlapping. (**Bottom**) Visualization of the predicted slope angles (y-axis) against the ground truths (x-axis). The average root mean squared error (RMSE), mean absolute error (MAE), and R^2 values are shown at the top. The model robustly generalizes to an unseen profile from 5- and 15-degree slopes.

gles have different data distributions and are largely non-overlapping.

The visualization suggests that we could train a neural network to predict the inclination given the time series of sensor readings. Figure 3 (bottom) shows the prediction result of the CNN model trained with data collected from 0, 10, and 20-degree slopes. The model achieves great prediction performance with both training and unseen test data collected under different steepness angles of 5 and 15 degrees. Specifically, it achieves the mean absolute error (MAE) of only 1.5 degrees for the prediction of unseen test data. All these results validate the reliability and usefulness of our proposed sensor design.

4 Discussion and Conclusion

We propose a novel triaxial force sensor design aimed specifically at measuring the foot-ground interaction of legged robots. The design utilizes the 3D Hall-effect sensor for accurate measurement and is compliant thanks to the deformable O-ring configuration. To assess the reliability and practicality of the proposed design, we analyze the sensor readings collected under varying slope angles. The results indicate that the magnetic field profile aligns with GRF trends observed in previous studies. Furthermore, we demonstrate that the sensor readings can be used to train a neural network to accurately predict slope angles, reinforcing the reliability of the sensor data.

References

[1] H. Zhang, R. Wu, C. Li, X. Zang, X. Zhang, H. Jin, and J. Zhao, “A force-sensing system on legs for biomimetic hexapod robots interacting with unstructured terrain,” *Sensors*, vol. 17, no. 7, 2017. [Online]. Available: https://www.mdpi.com/1424-8220/17/7/1514

[2] P. Billeschou, C. Albertsen, J. C. Larsen, and P. Manoonpong, “A low-cost, compact, sealed, three-axis force/torque sensor for walking robots,” *IEEE Sensors Journal*, vol. 21, no. 7, pp. 8916–8926, 2021.

[3] W. Haomachai, D. Shao, W. Wang, A. Ji, Z. Dai, and P. Manoonpong, “Lateral undulation of the bendable body of a gecko-inspired robot for energy-efficient inclined surface climbing,” *IEEE Robotics and Automation Letters*, vol. 6, no. 4, pp. 7917–7924, 2021.

[4] A. Krizhevsky, I. Sutskever, and G. E. Hinton, “Imagenet classification with deep convolutional neural networks,” *Advances in neural information processing systems*, vol. 25, 2012.

[5] L. Van der Maaten and G. Hinton, “Visualizing data using t-sne.” *Journal of machine learning research*, vol. 9, no. 11, 2008.