

Spatial Tracking with Wearable Sensors

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Group 52

Problem Description

Tracking human body motion has multiple applications in robotics, fitness, and medical fields. The advancement in low cost sensors makes it possible to develop affordable products; however, the sensor accuracy suffers. Our project focusses on using magnetometer readings to model the human body motion and investigates the dynamic errors that are prominent in indoor environments with lots of ferromagnetic interferences.

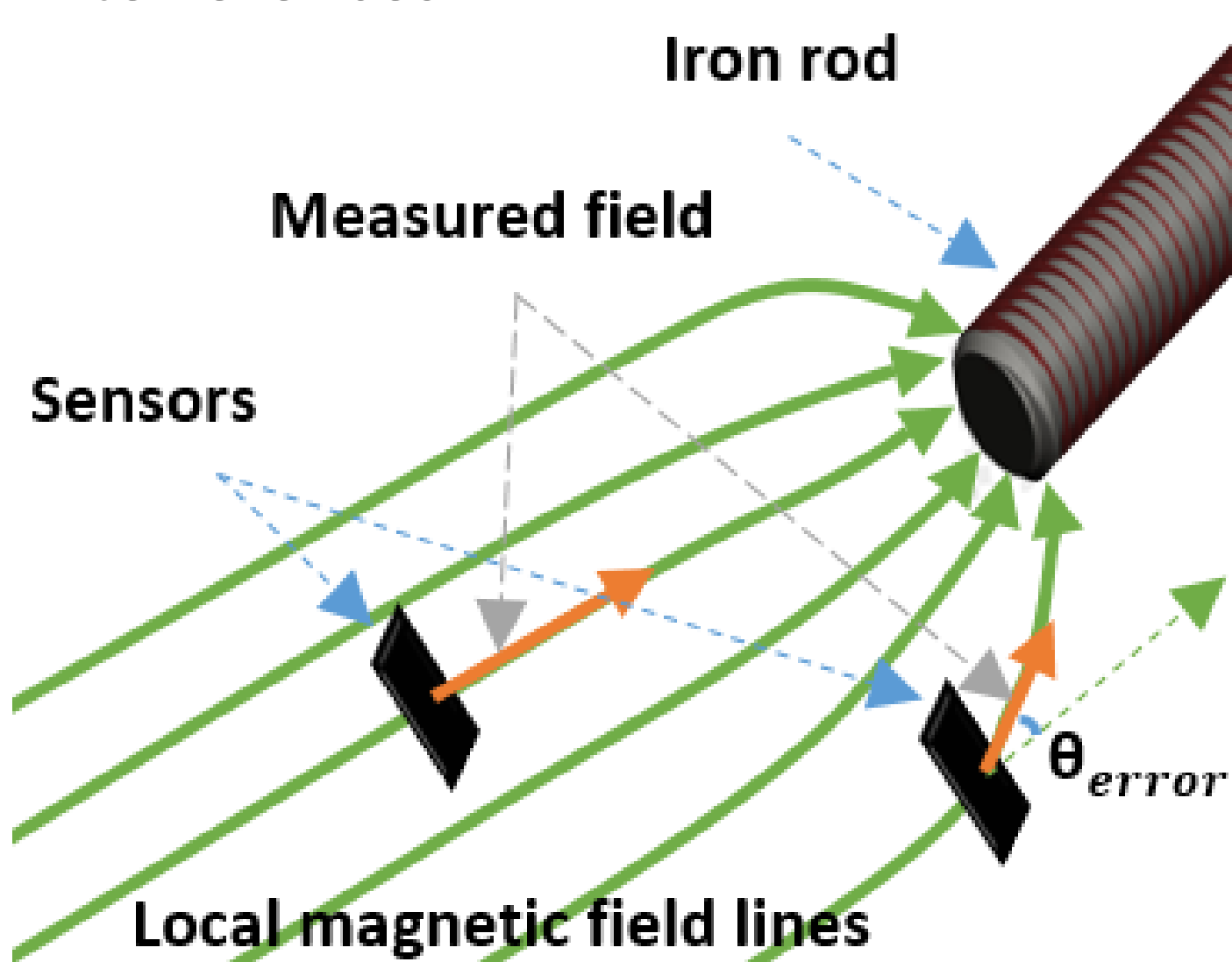


Fig. 1. Distortion of earth's magnetic field near an iron rod

Proposed Solution

Our solution investigates the effect of hard and soft iron errors in two use cases: squats and treadmill exercises. Our design has the following features:

- Wireless capability (up to 20m)
- Supports multiple sensors
- Real-time data plotting and animation
- Cross platform compatibility – Linux, Mac and Windows



Fig. 2. Wearable prototype with Bluetooth module and multiple sensors

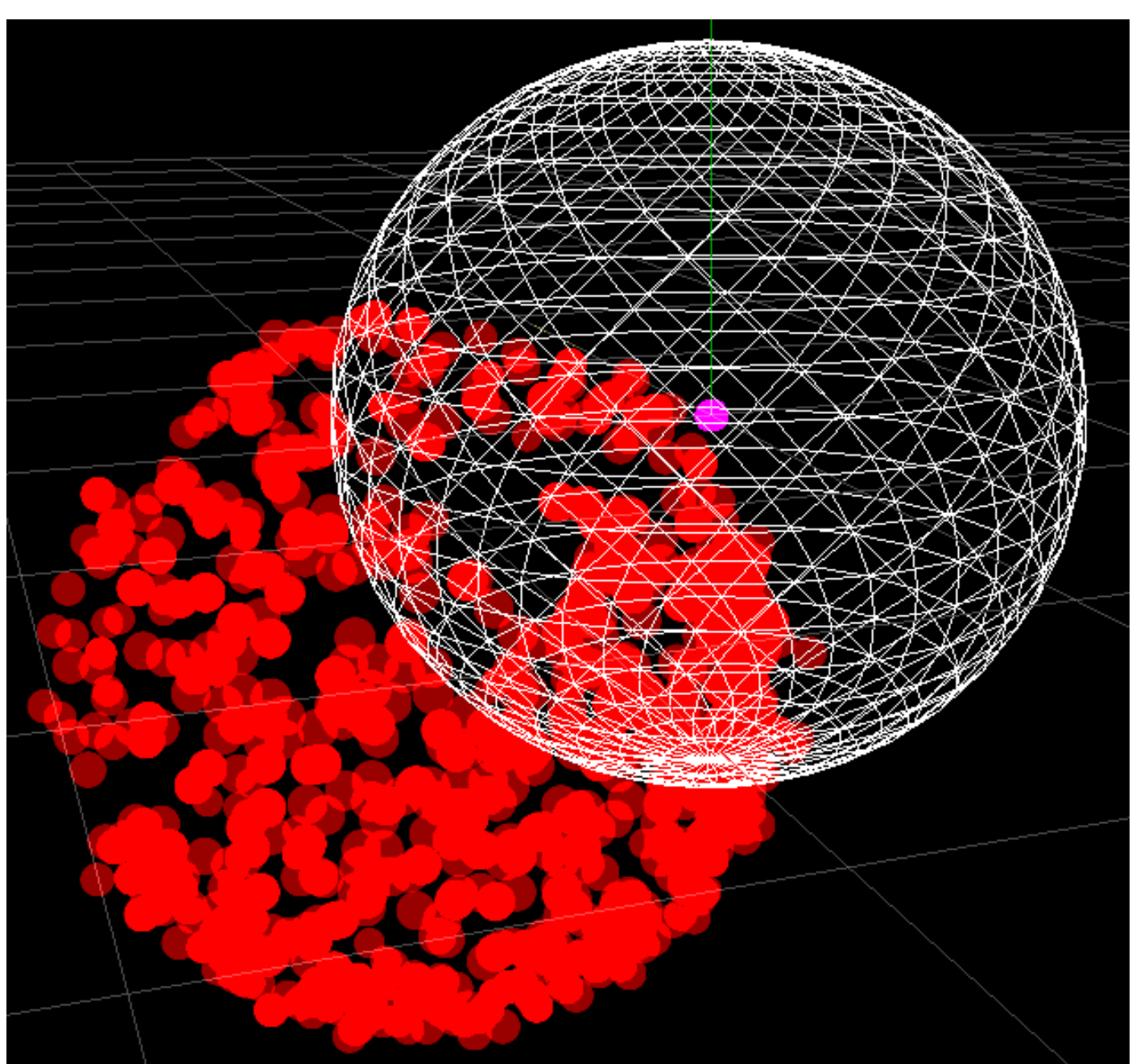


Fig. 3. Real-time sensor data plot

Methodology

The Ellipsoid Fitting Algorithm is chosen to mitigate soft iron and hard iron errors. Ideally, magnetometer data should be isotropic; therefore, a sphere can be visualized after the calibration has been applied.

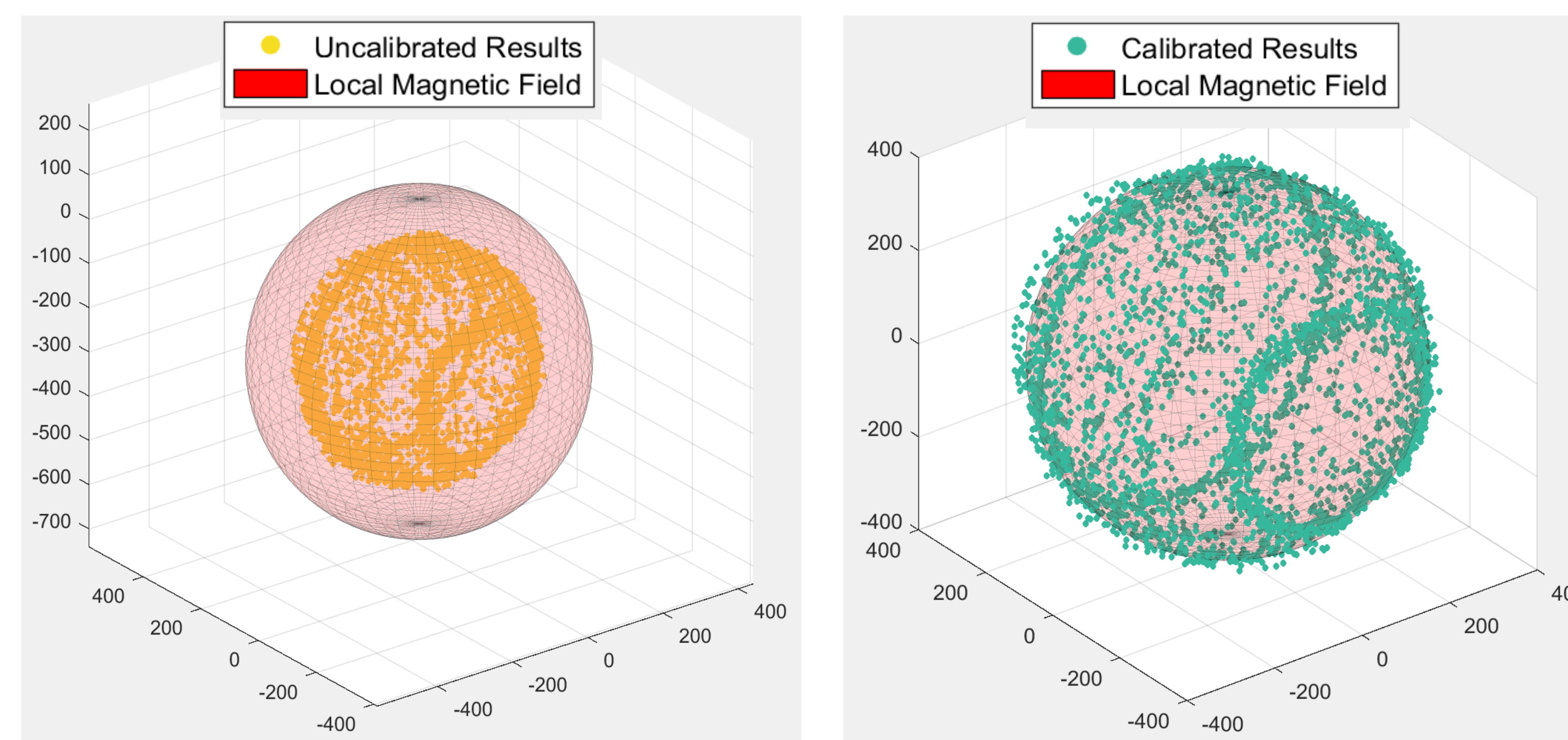


Fig. 4. Magnetometer calibration: (left) un-calibrated; (right) calibrated

The Ellipsoid Fitting Algorithm can be characterized by the formula [1][2]:

$$\mathbf{H}_{cal} = \mathbf{A}_{scale}^{-1}(\mathbf{H}_{uncal} - \mathbf{B}_{bias})$$

Where:

- \mathbf{A}_{scale}^{-1} is the scaling matrix of x, y, and z magnetometer readings
- \mathbf{H}_{uncal} is the uncalibrated magnetometer readings
- \mathbf{B}_{bias} is the hard iron offset of the sensor
- \mathbf{H}_{cal} is the calibrated magnetometer readings

Verification and Testing

Arm tracking experiment

An experiment to track the position of an arm was conducted. The test subject repeatedly bent their arm vertically from 0 to 90 degrees. After calibration, the algorithm significantly improved the dynamic motion accuracy.

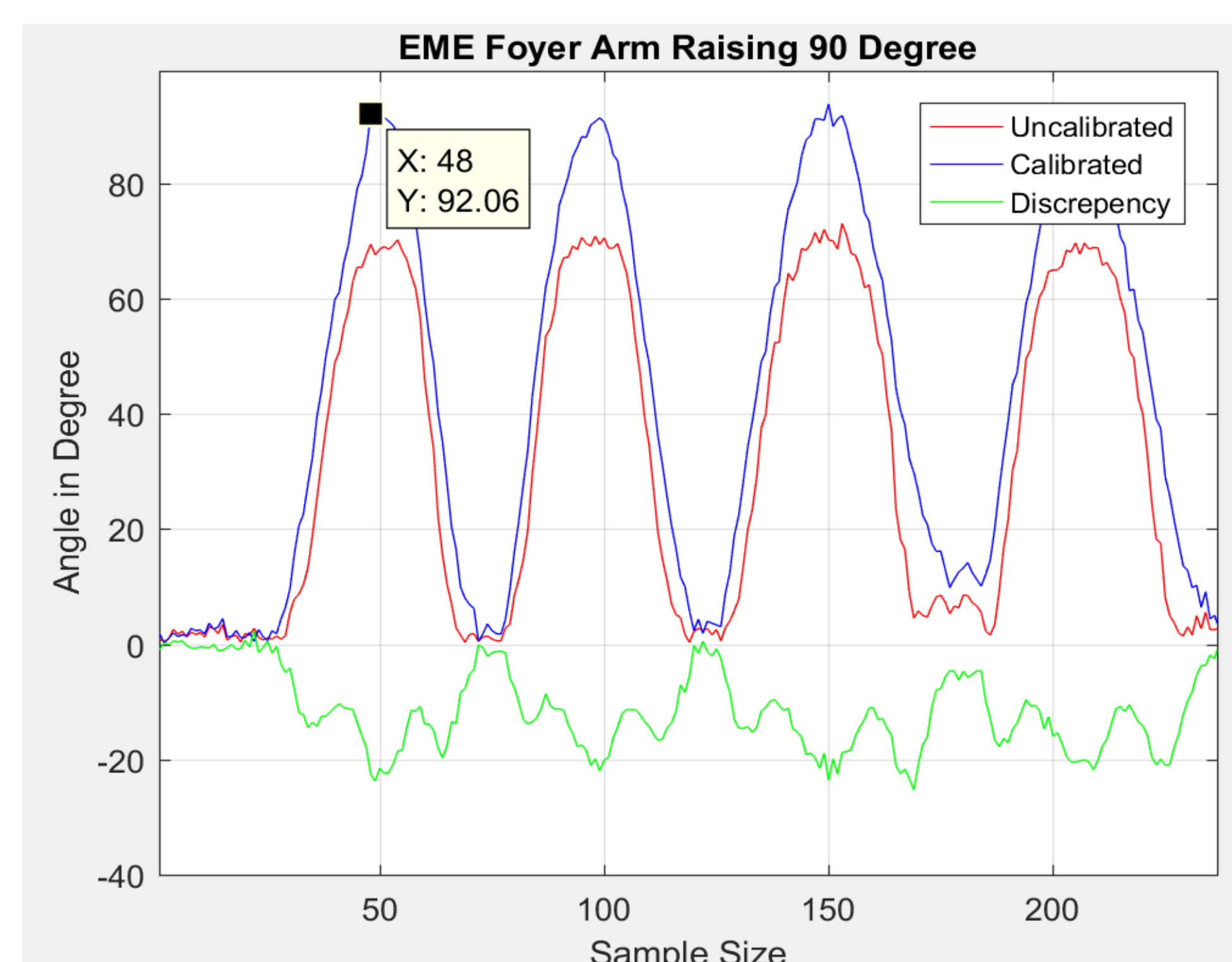


Fig. 5. Arm tracking experiment



Proximity to metallic objects

We also analyzed the impact of iron objects to the sensor readings as a function of distance. Figure 6 shows that the closer an iron object is to the magnetometer, the greater the error in the measured data.

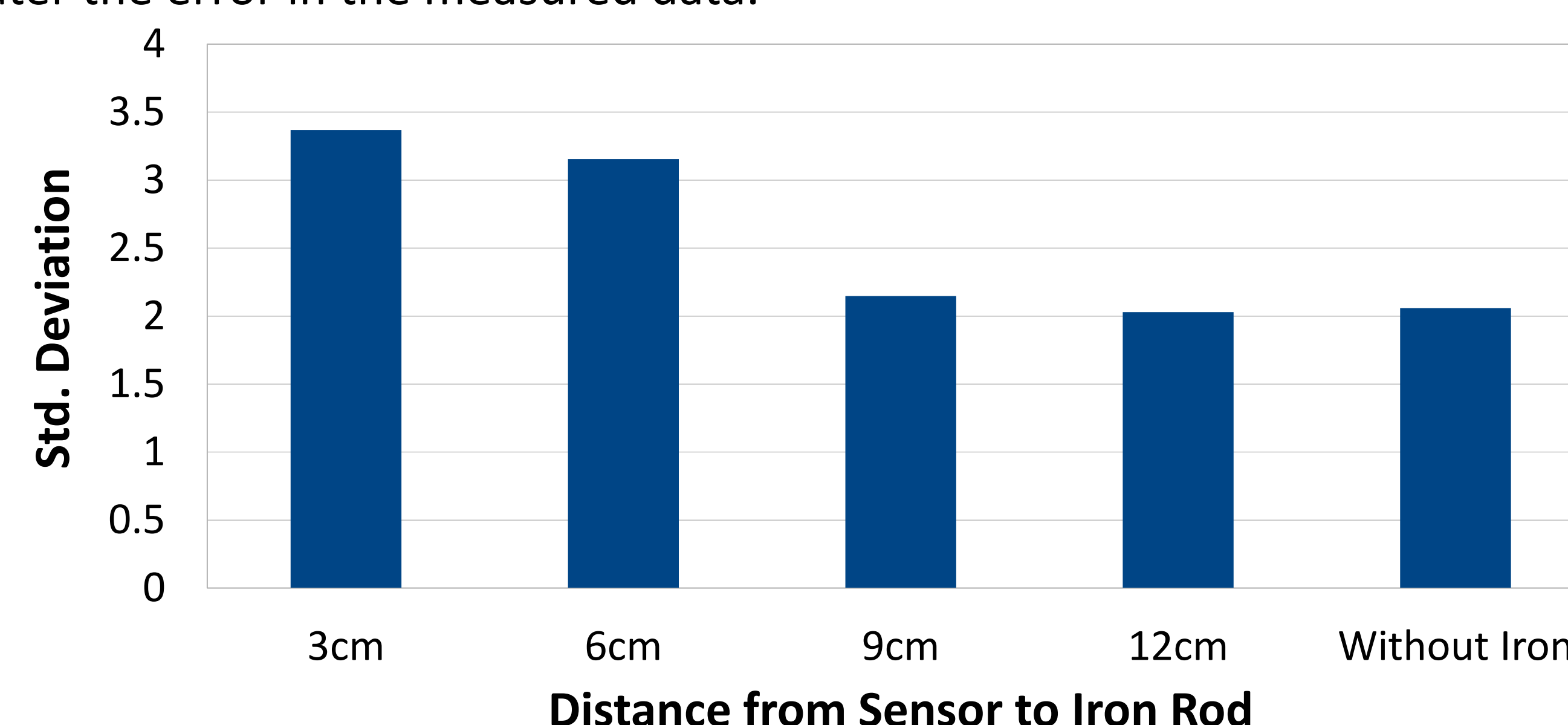


Fig. 6. Errors in data with varying distances of iron rod from the sensor

Treadmill and squat tests

We conducted dynamic tests where the subject walked on a treadmill and performed squats (see Fig. 7 & 8). The measurement data was used to recreate an animation of the motion.

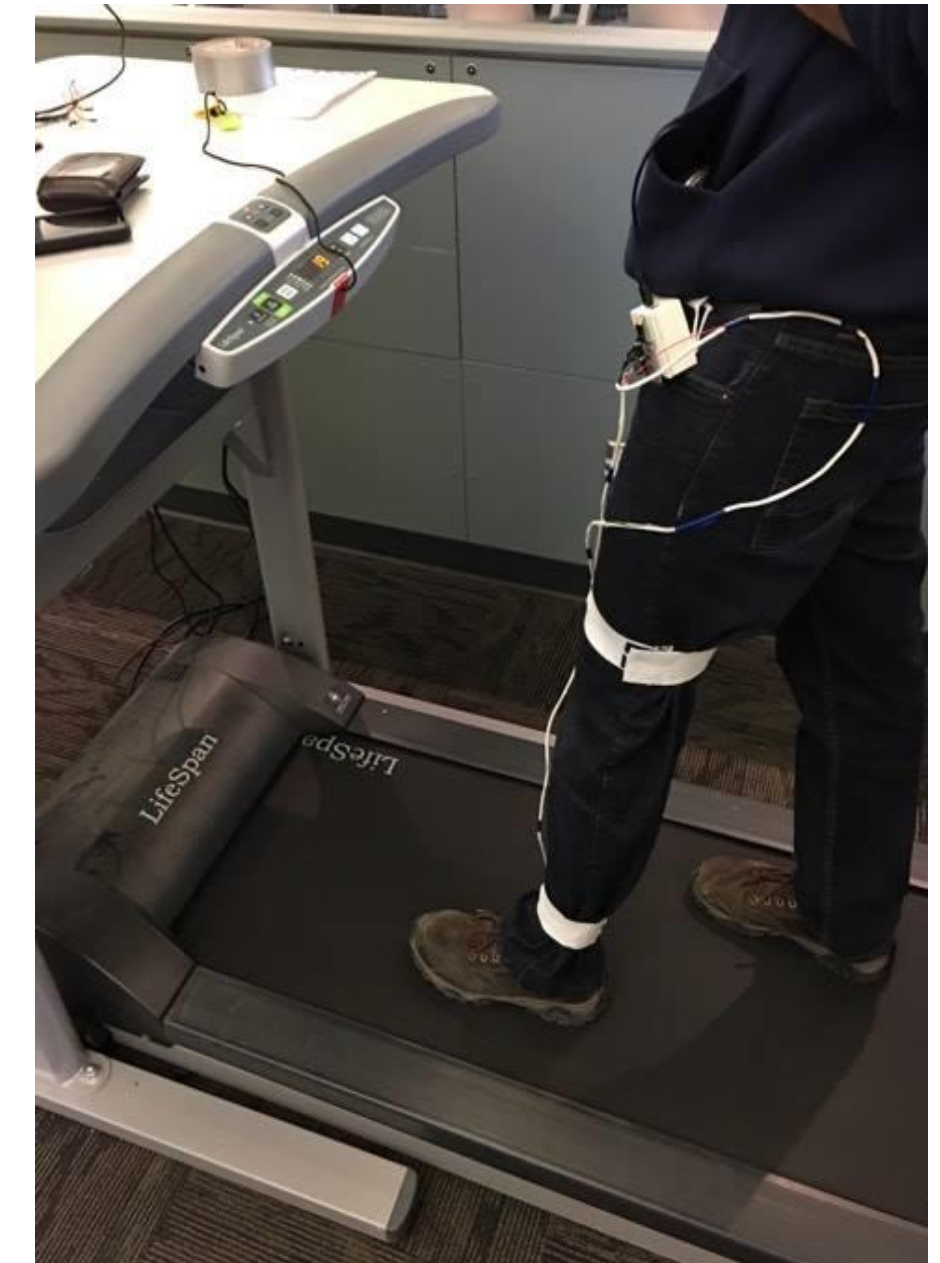


Fig. 7. Treadmill test

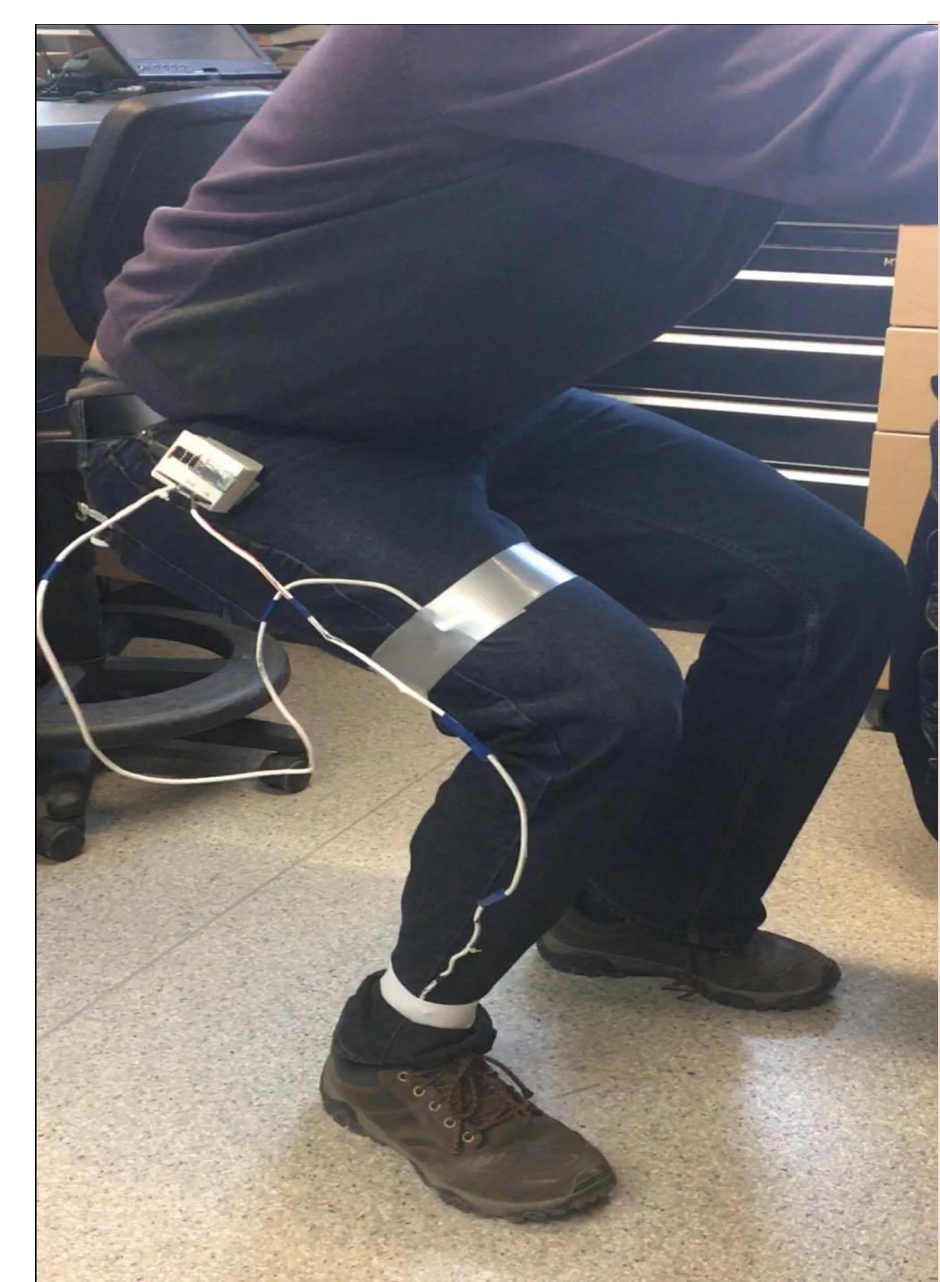
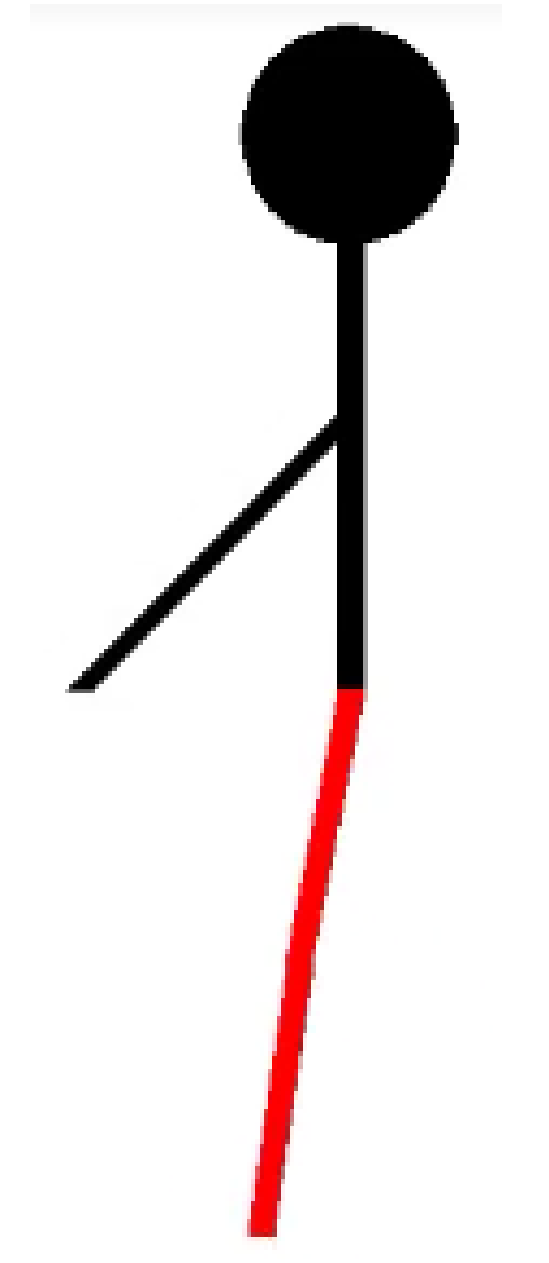


Fig. 8. Squat test



Future Improvements

- Analysing more use cases with more dynamic motion
- Visualizing sensor readings in the three dimensional plane could provide better demonstration

Conclusions

The **static calibration greatly improves the accuracy** of the magnetometer data. Despite the presence of ferromagnetic interferences, the stickman animation demonstrated that we were **able to model the human body motion accurately** using magnetometers.

Reference

- [1] Li, Qingde, and John G. Griffiths. *Least Square Ellipsoid Specific Fitting*. 1st ed. IEEE Xplore, 2004. Print.
- [2] Ozyagcilar, Talat. *Calibrating an eCompass in the Presence of Hard- and Soft-Iron Interference*. 1st ed. NXP, 2015. Print.

Acknowledgement

We would like to express our gratitude to T. Johnson for providing us laboratory access and T. Giesbrecht for the 3D printing and our industry sponsor for providing the necessary assistance.