# Final Report - IMU-Based Indoor Localisation

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## I. Introduction

AngelCorp has contacted designers to develop a prototype system to monitor the location and safety of its factory employees. This system will use an inertial measurement unit (IMU) equipped with accelerometers, magnetometers, and indoor localisation techniques. Before delving into system design, a literature review will provide insights into the approaches and performance evaluation methods to guide the prototype's development. From there, the implementation of this prototype system will be explained. In particular, the implementation of the heading calculations and step detection algorithms. Additionally, the system will be evaluated, and the future considerations of the system will be discussed.

## II. Literature Review

### A. Sensor Calibration and Data Processing Methods

Sensor calibration and data processing is a crucial step in IMU-based localisation. These techniques serve as the foundations for accurate and reliable indoor localisations. Any bad-quality data processed from the sensors within the IMU will propagate through the system, resulting in the inaccurate tracking of people in an indoor setting. Hoflinger *et al*. [1] proposed the Micro-IMU, a wireless IMU designed to minimise the weight, size and power consumption while retaining performance comparable to commercially available wired IMUs. To ensure their sensors do not contain any biases while in operation, they calibrated the gyroscope and acceleration sensors by keeping the sensor model still for a period and calculating the average bias [1]. They also calibrated the magnetic field sensor by finding the best 3D ellipsoid of the magnetic field that fits the sensor data set using the Merayos technique [1]. Once all the sensors have been calibrated, they remove noise by applying a second-order low-pass filter [1]. These techniques ensure that their sensed data is bias-free and stable.

On the other hand, Chattha and Naqvi [2] found that Pedestrian Dead Reckoning (PDR) schemes using IMUs are severely affected by the placement of the IMU on a person and error accumulation over time [2]. They suggested a smartphone-based indoor localisation solution, the Precise Indoor Localisation Technique (PILoT), to address the limitations of PDR [2]. Using wavelet filtering, Wavelet transform, they can reduce the acceleration noise produced by variations in a person's natural step frequency and external noise.

Sensor data fusion can also handle noise reduction and improve accuracy. Zhang *et al*. [3] proposed a wireless, lightweight IMU with integrated ultra-wideband (UWB) technology to improve the accuracy of indoor localisation. In this research, they implemented a noise cancellation algorithm, the Mahony complementary filter, when fusing all their gyroscope and accelerometer sensor data. The two sensors estimate the attitude and position of the person holding the IMU. Implementing this data fusion noise cancelling algorithm will ensure the accuracy of tracking a person's position in a 3D space.

All three papers [1], [2], [3] highlight the Kalman filter as a critical sensor data fusion algorithm. It combines data from various sensors in the system, such as acceleration and gyroscope, highlighted in [2]. The combination of sensors would produce more accurate results than an individual sensor's result.

Kalman filter can also be used to integrate the data from two systems, like the fusion of IMU and UWB mentioned in [3]. Zhang *et al*. [3] found that the data from the IMU is reliable for only short periods; as time progresses, more errors accumulate. While UWB's positioning data may have deviations due to asynchronous clocks, it does not accumulate more errors as time progresses. Using an iterative compensation of the positioning data from IMU and UBW via the Kalman filter, it would be possible to achieve higher precision for indoor positioning [3]. Higher precision would especially be critical for tasks like step detection and pedestrian tracking, where precise sensor information is required.

### B. Step Detection Methods

Step detection, or gait analysis, identifies and counts the number of steps a user has taken while the IMU is mounted to a person's foot. This detection is usually through algorithms analysing accelerometer readings for a signal indicating bipedal motion. In Zhang *et al.* paper [3], one gait step has two parts: when the foot touches the ground and when the foot is swinging or moving. They considered that the acceleration and velocity of the foot will be zero when it touches the ground [3]. However, since there is noise from the IMU's accelerometer, some error will be introduced, so the actual acceleration is a non-zero value. To eliminate the error, they utilised the Zero-Velocity Update (ZUPT), which was used in two other papers: [1] and [4].

The ZUPT algorithm detects when the foot is on the ground and resets the acceleration and velocity to zero. All three papers, [1], [3] and [4], used the 3D data from the gyroscope and a threshold value to inform the ZUPT algorithm when a foot is on the ground. When the gyroscope data is smaller than the threshold, it indicates that the foot is on the ground and the velocity needs to be reset. However, Bai *et al.* [4] added an Extended Kalman Filter (EKF) on top of ZUPT to improve position accuracy. These techniques combined form a conventional pedestrian positioning framework called IEZ [4].

Bai *et al.* [4] propose two contributions to the indoor localisation field: a motion speed-based adaptive gyro error compensation (MSAGEC) scheme and a step detection method based on up/downstairs tracking (SDUDT) without the use of a barometer. Considering that Bai *et al.* [4] aim to tackle the IMU indoor localisation of people walking up and down stairs and be able to detect motion speed adaptively, they also require additional techniques to capture an accurate horizontal position and height estimation. These techniques are Zero Angular Update (ZARU), Heuristic Drift Reduction (HDR) and Zero-Velocity Height Update (ZHU) [4].

On the contrary, Chattha and Naqvi's [2] research does not require the smartphone with IMU placed on a person's foot as traditionally done for step detection. However, this research attempts to detect steps when a smartphone is placed in a person's trouser pocket or held in their hand. Due to this, they classified the movements into two categories: stride orientation and step orientation. Stride orientation captures the swinging phase of bipedal motion, while step orientation captures the foot touching the ground [2]. They also noted that one stride equals two steps in their research [2]. To determine the device orientation of a person, they used Wavelet transform. Using that information, they took a more straightforward approach to step detection and step length estimation. From their observations, the accelerometer's x-axis and z-axis are more sensitive to differences in device orientation [2]. Based on those measurements, their step detection algorithm increments the step count if the difference between the highest and lowest peaks exceeds their noise threshold.

### C. *Performance Evaluations Methods*

Experimental results and evaluations are critical to verifying indoor localisation research. Each paper employs practical tests involving participants walking specified distances or predetermined paths with the IMU on their person. However, only three papers, [1], [3] and [4], have verified their results through experimentations with an IMU positioned at the participant's feet. Hoflinger *et al*. [1] held experiments that tracked a 30-metre walk within a building with their Micro-IMU mounted on the participant's foot. The results showed a maximum deviation of one metre from the actual track.

Conversely, Zhang *et al.* [3] experiments of measuring one-step walking were intended to verify the positioning accuracy of the IMU and UWB modules. A participant took a single step 20 times while having a sensor device fixed to their foot to measure the step size. From those measurement results, they concluded that the IMU and UWB average errors were 4.02 cm and 4.70 cm, respectively [3].

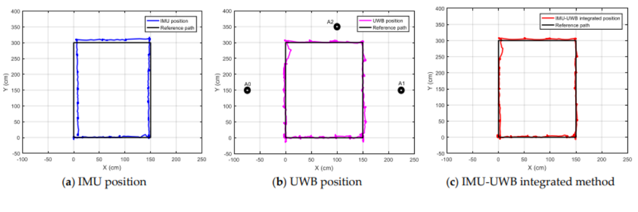


Fig. 1. Measurement locations of walking along a rectangular path where blue, pink, and red lines indicate sensor position, and the black line is the actual path [3].

They conducted another experiment to verify the localisation accuracy. Participants in this experiment were to walk along a rectangular path and an arbitrary path within an indoor environment [3]. This experiment was repeated three times, each using a different technology: IMU only, UWB only and their IMU-UWB integrated method. In the rectangular path, they found that the integrated IMU-UWB method does seem to take the best of both technologies to provide a more accurate and stable localisation result, as seen in Fig. 1 [3].

In the arbitrary path, they set up a bean-like shape on the floor for participants to follow. Transmission through Bluetooth was used to send the measured positioning data from the sensor device to the PC for evaluation and analysis for each method [3]. From this experiment they concluded that their integrated IMU-UWB method has an average position error of 7.58 cm compared to 11.59 cm and 12.46 cm for IMU and UWB respectively [3].

Similarly, Bai *et al.* [4] experimented with a flat rectangular path. However, instead of comparing different technologies, they compared different motion speeds and travel distances to verify their MSAGEC scheme against the existing combination of IEZ, ZARU and HDR methods [4]. The respective travel distances they used for their experiments were 48 m, 153.6 m, and 224.6m, and motion speeds were 1.2m/s for slow walking, 1.6m/s for fast walking and 2.2m/s for running [4]. Participants in this experiment were to move along a rectangle path at different motion speeds. These experiments found that both methods gave identical results of 0.42% closed error and 0.22% distance error [4]. However, when it came to fast walking, the closed error was reduced from 6.22% to 3.53% [4]. They discussed that the significant error was that both methods used a fixed threshold of when the foot was on the ground, which was more suitable for slow walking. Verification of their SDUDT was by conducting experiments of walking up and down stairs for three levels and five levels [4]. In this experiment, they found their height error was 0.52% due to variations in star heights [4].

Contrary to the other three papers, Chattha and Naqvi's [2] experiments and analysis did not require their smartphone IMU to be placed on a foot to verify their step detection algorithm using wavelet filtering. Instead, they experimented with swapping placements of the smartphone, from hand to pocket, while taking 50 steps [2]. This experiment was conducted ten times, where the smartphone was in a different location each time [2]. From this experiment, the average number of detected steps was 49.9, an accuracy of over 99% [2]. To verify their positioning algorithms using map awareness, participants walked randomly in a building from a known reference and returned to the start position. The distance covered by participants ranged from 60 to 150 metres [2]. An error value is calculated from the estimated final position from the system and the actual start location. This experiment was conducted 80 times, resulting in a mean error of 0.52 m [2].

## III. Implementation

This section covers the implementation details of the indoor localisation system proposed by AngelCorp using a SensorTile development kit, STEVAL-STLKT01V1. I will delve into the process of extracting the magnetometer's sensor data and use it to calculate the relative heading angle of a person. Using this relative heading and accelerometer data, I use it to detect the steps of a person walking using a step detection algorithm and find the real-time positioning. I will also detail the performance analysis of the system and address any limitations that the system has.

## A. Heading Calculation

Calculating the heading or angle of direction of the user utilises the magnetometer sensors, which detect the magnetic field of the surroundings. First, the magnetometer is initialised to 100Hz high-resolution operating mode, with temperature compensation. The built-in offset cancellation and low pass filter are also enabled for this sensor. The magnetometer sensor's X, Y and Z axis is read every 100 milliseconds and a sensitivity of 1.5 is applied to those values. This ensures that the X, Y and Z axis values are in milli-Gauss.

However, only the X and Y axis values are required to calculate heading angles. The equation used for this calculation is $heading = \arctan\left(\frac{magY}{magX}\right) \times \frac{180}{\pi}$ , where magY and magX are the y and x-axis values of the magnetometer sensor, respectively. Since the C function for arctan sometimes gives different values compared to a calculator, the heading value will decrease by 180°. If the heading calculated is a value below zero, the heading will increase by 360°. This ensures that the heading value is between 0 and 359 degrees.

The heading calculation is called at the very start of the program and every time the magnetometer sensor is being read. The system calculates the heading at the program's start to get the user's initial heading angle. This initial heading will be used as a reference point to calculate the relative heading angle to determine the user's orientation as they walk around the room. Additionally, at the program's start, the relative heading angle will be set to zero.

The relative heading angle is calculated every time the program reads the magnetometer. The calculation used to find the relative heading angle is $relative\ heading = current\ heading - initial\ heading$ , where current heading is the raw heading angle at that time relative to the Earth's magnetic field, and the initial heading is the angle relative to the Earth's magnetic field at the start of the program. To ensure that the relative heading angle is between 0 and 359 degrees, the system increases it by 360° if the value is negative.

## B. Step Detection Algorithm

A step detection algorithm using accelerometer data and heading angles is used to determine the X and Y coordinates of a person walking along a path. Firstly, the accelerometer is initialised to 100Hz at a high accuracy mode with ± 2g. The accelerometer sensor's X, Y and Z axis is read every 100 milliseconds. From there, the accelerometer data is averaged using a moving window. This moving window takes 10 of the most recent samples from the accelerometer and calculates the average. This results in a smoother signal and increases the accuracy of detecting steps.

After experimenting with the accelerometer, I noticed that the Z-axis values often pass an average threshold of 1070 mili-G's whenever I take a step. So, I utilised a peak detection algorithm to find a Z-axis acceleration data that surpasses that threshold value. To avoid getting false positives in this detection algorithm, the system compares the current and previous times when a step was detected. If the time difference exceeds the minimum interval of 800 milliseconds for a step, the system confirms a new step.

Once a new step has been confirmed, the relative heading calculates the total distance. To find the total X position of the user relative to their starting point, I used this equation: $total\ X\ distance = \sum Stride\ Length \times \sin(relative\ heading \times \frac{\pi}{180})$, where Stride Length is the distance covered in a single step in centimetres, 70 centimetres in this case. The total distance in the X position is the west and east direction of the user relative to the starting point. This means that a positive x value would indicate the user has travelled more to the west, while a negative value indicates an eastward direction.

Similarly, to find the total Y distance relative to the starting point, this equation was used: $total\ Y\ distance = \sum Stride\ Length \times \cos(relative\ heading \times \frac{\pi}{180})$ . The total Y distance is used to determine the north and south direction of the user. If the Y position is positive, the user has travelled northwards relative to their starting position, while a negative value indicates a southward direction. Both equations used to find the total X and Y distances require the relative heading to be converted back into radians from degrees.

## C. Performance Analysis

To evaluate the performance of my system, I tested walking in a straight line with a measuring tape as a guideline. I looked at the Y position sent through Bluetooth at each step and compared it with the tape measure value. The Y distance covered in these experiments were 300cm and 600cm. In this experimentation, I found some of my Y positioning was off by 4%, as seen in Fig 1.

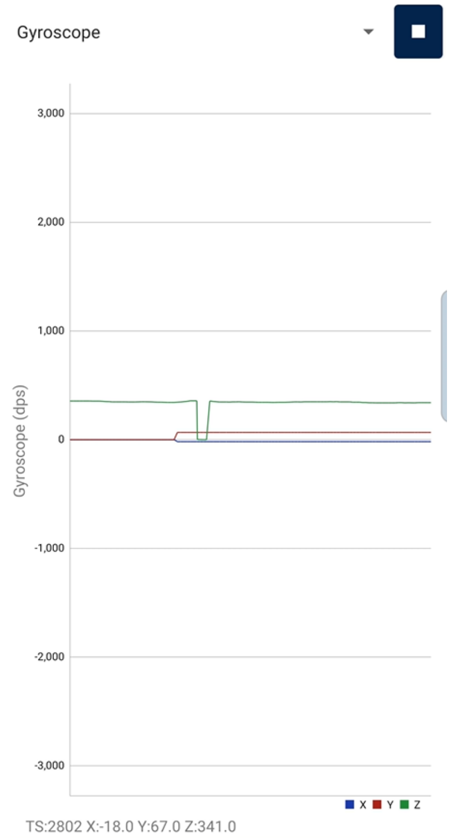


**Fig 1.** Testing the X and Y position of taking a step and the heading angle (Z). The actual step should have a Y value of 70 cm.

However, I noticed that the X position is not always consistent when walking straight, as seen in Fig 2. In the same experiment as Fig 1, I noticed that the X position changed from 18cm eastward to 48cm eastward in Fig 2 while walking in a straight line.

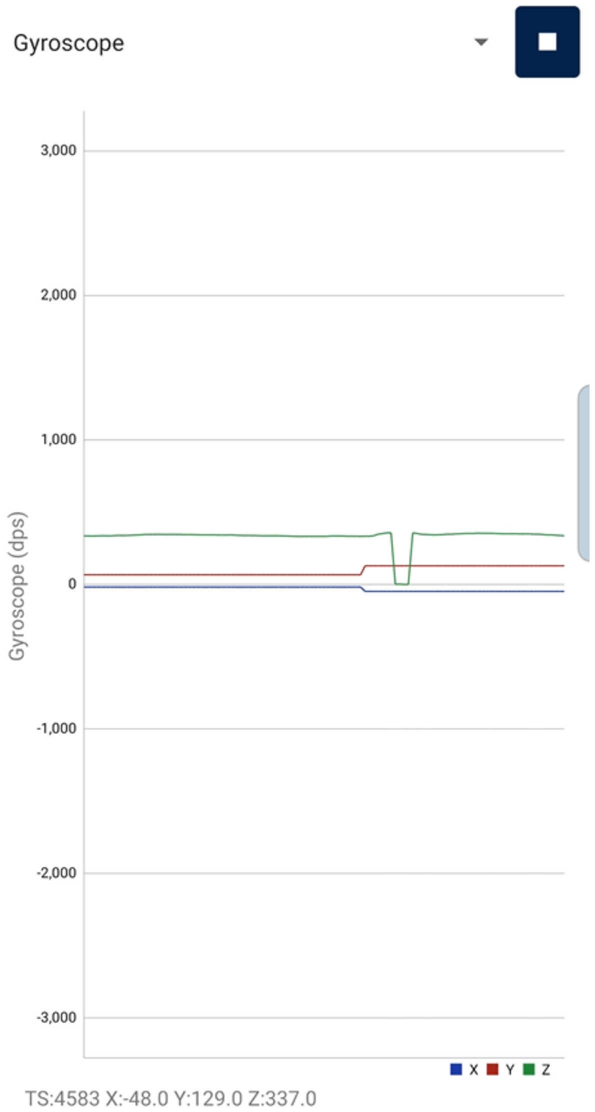


**Fig 2.** Testing the X and Y position of taking a step and the heading angle (Z) following Fig 1. The actual step should have a Y value of 130 cm.

One plausible explanation for this shift in the X position may be the slight shift in orientation. Fig 1 and Fig 2 capture the change from 341 to 337 degrees, which can cause fluctuations in the X position. This orientation change may be because the sensor is held in my hand rather than tied to a shoe, like in the literature. When the sensor is held in a hand, it can introduce minor orientation changes due to natural hand movement or tilting. The orientation changes affect the recorded relative heading angle and the X position.

The orientation drift can also be due to magnetic interference by external sources such as electronic devices and metal objects. External sources of magnetic interference can impact the accuracy of the magnetometer's readings. This makes those readings deviate from the Earth's magnetic field and cause inaccuracies in heading and positioning calculations.

### *D. Future Considerations*

As mentioned in the performance analysis, further accuracy of positioning data and relative heading angles can be optimised in this system. The minor orientation drifts due to hand movements can be mitigated by a filter such as the Kalman filter to reduce its sensitivity. When experimenting, it may also be helpful to tie the sensor to a shoe to minimise the orientation errors.

Magnetic sensitivity can also be reduced to remove the magnetic interference from external sources. To mitigate magnetic sensitivity, calibrations to the magnetometer may be required to ensure accurate baseline measurements. Additionally, implementing a filter like the Kalman filter can help reduce the impact of magnetic interference to enhance the system's robustness.

## IV. CONCLUSION

In this report, the literature review has explored vital aspects of IMU-based indoor localisation, such as sensor calibration and data processing, step detection methods, and performance evaluation techniques. These methods are crucial for accurate and reliable indoor localisation. Different methods were discussed, from sensor calibration and noise reduction to step detection methods using ZUPT. Sensor data fusion, especially the Kalman filter, improves accuracy by combining sensor data. Performance evaluations through following a specified path provide valuable insights into verifying the validity of this project.

Additionally, implementing an indoor localisation system utilising the SensorTile development kit was detailed. This system utilises magnetometer sensor data to calculate the relative heading angle and an accelerometer for step detection algorithm to determine a user's real-time positioning.

While the system exhibits promising capabilities, there are areas of improvement. There were issues with minor orientation drift induced by hand movements and magnetic sensitivity resulting from external interference. Due to this, system accuracy and reliability can be further improved by filtering techniques like Kalman Filter and sensor calibration.

## REFERENCES

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