Performance Testing of PDR using Common Sensors on a Smartphone

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Abstract— Personal positioning system needs portable, flexible, and inexpensive sensor. Nowadays, most of smartphones in the market have been equipped with accelerometer and magnetometer to support some basic features. Utilizing these sensors as a positioning system is an interesting proposition because it doesn't depend on outside infrastructures and can be widely used by many people with their smartphone.

In this study, accelerometer and magnetometer sensor are used to estimate pedestrian positions based on dead reckoning method. Dead reckoning is a positioning method where subsequent position is estimated by adding displacement to the previous position. Moreover, our system is not only utilizing smartphone as an input sensor, but also implementing PDR (Pedestrian Dead Reckoning) in real-time mode in the smartphone that has limited resources.

Our experiment was performed with 30 test subjects, walking in 3 tracks with distances of 51.54m, 77.79m, and 82.67m respectively. The result shows that the system was able to estimate user position with average error less than 4.4% of total distance.

***Keywords*— accelerometer, magnetometer, pedestrian dead reckoning, sensor-based positioning system, smartphone**

I. INTRODUCTION

Tracking position of a person can be done using GPS (Global Positioning System). GPS provides an absolute position through passive ranging from four satellites navigation. However, the main limitation of GPS is lack of signal continuity. When someone enters a building or his position is between skyscraper buildings, the satellite signals can be blocked, attenuated, or reflected [1].

An alternative to track someone's position without depending on satellites navigation is Dead Reckoning (DR) method. DR method finds how far the displacements from the previous position. In pedestrian tracking, this method is known as Pedestrian Dead Reckoning (PDR). The displacements of pedestrian can be determined by estimating the total steps and the length of each step. The aforementioned method can be measured using acceleration signal.

The integration of motion sensors on mobile phones tends to increase. According to [2], it is expected that 64% of total mobile phone on 2015 will be equipped by accelerometer and 48% of them will be equipped by compass sensor. This trend surely has a positive influence toward PDR implementation.

Utilization of sensors integrated in smartphone as navigation tools has some benefits, such as easy to use and carry everywhere and its price relatively more affordable than dedicated module sensors. Another benefit is that it is possible to track user's position in a real time and then show the current position at the time, because smartphone has its own processor and screen to perform the task and display the result.

However, this scenario will force the placement of smartphone hold in the hand in front of chest, so the user can observe current position in the phone screen. This placement leads to an additional interference in sensors sensing, such as reflect-movement that could affect the user's walking pattern. As a consequence, walking pattern on each individual can be different and may need a process to fit their walking pattern (i.e. through calibration process). This process will increase the accuracy of step detection, but making impractical and unfeasible for doing pre-walking to recognize walking pattern of person before doing the real trip/tracking.

Therefore, it is necessarily to develop the universal model of step detection. It leads to a system that can be used by general user without over fitting to an individual walking pattern.

The structure of this paper is as follows: Section II describes related works in the field. Methodology and experimental result will be described in Section III and IV. Finally, we conclude our study in Section V.

II. RELATED WORK

Many smartphones in the market usually equipped with accelerometer and magnetometer sensor to support the basic features, such as auto screen rotation and digital compass. These sensors can be used to develop tracking system that works as a pedometer, counting number of steps as representation of pedestrian displacement. The user only needs to download and install the software application on such mobile devices without an extra effort to purchase and install the dedicated hardware sensors. However, according to [3], this approach has some drawbacks. Firstly, these low cost sensors in mass-market devices are normally noisier and the resulting dead reckoning estimation is subject to faster error accumulation. Secondly, such low cost sensors have lower rate in updating/refreshing their readings. Moreover, such mobile devices cannot be placed on the foot, which usually do not experience any zero-velocity phase during a step.

The raw data obtained from phone sensors can be processed online or offline. Some previous researches [3], [4] used sensor integrated in smartphone only to obtain raw data and then process them in the PC, not directly on the phone. This process also called as offline processing because it does not give a real-time result. Offline processing is relative easy to implement because a system has known the overall signal pattern while it is proceeded. Other researchers [5], [6], [7], [8], [9] not only obtain raw data from the sensor, but also use smartphone processor to process the data and then show the result real-time on the phone screen. This online processing is more challenging since the overall signal context is unknown while it is processed.

In order to detect the pedestrian movement, it is necessary to know when a valid step is occured. There are two common methods to detect step, namely zero-crossing method [4], [7], [10] and peak-detection [3], [6], [8], [9], [11]. The zero-crossing method detects how many steps were taken by processing the fluctuating accelerations, which cross zero twice with every step. Researchers usually use time-interval threshold between two zero crossing points to reject the invalid-detected step. The other method is known as peak detection method. This method detects a valid step based on some acceleration peaks.

According to [11], the human walking phase is divided into a swing phase and a heel-touch-down phase, as shown in Fig. 1. During the swing phase, the vertical acceleration will show a negative peak, which is then followed by a positive peak and again a negative peak due to the heel-touch-down phase [8].

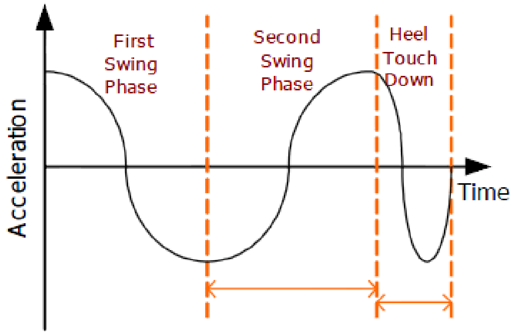

Fig. 1 Acceleration signal pattern in human walking phase

Study in [6] did the real-time computational process in smartphone, with additional gyroscope sensor and combining fingerprint Wi-Fi technique. In case of step detection, they implement peak detection method with static threshold scheme. According to [12], determination of static threshold to detect valid step is not easy for reliable step detection, since the pattern of impact signal depends on type of movement and type of ground over which the person walks. The variation of walking style person to person also influences to the variation of spring in the steps [10]. Therefore, inappropriate static threshold determination could decrease the accuracy because of imprecise step detection. In order to minimize the effect of inappropriate static threshold, [5] calculates the threshold according to the sensory data at the sampling phase for each user. However, there is inefficiency if every user must do the calibration process before they use the system.

In this study, step detection was performed with universal model that could be used by all test subjects, therefore this system could be used efficiently without calibration process to adjust users walking pattern.

III. Methodology

A. System Design

The workflow of the system is shown in Fig. 2.

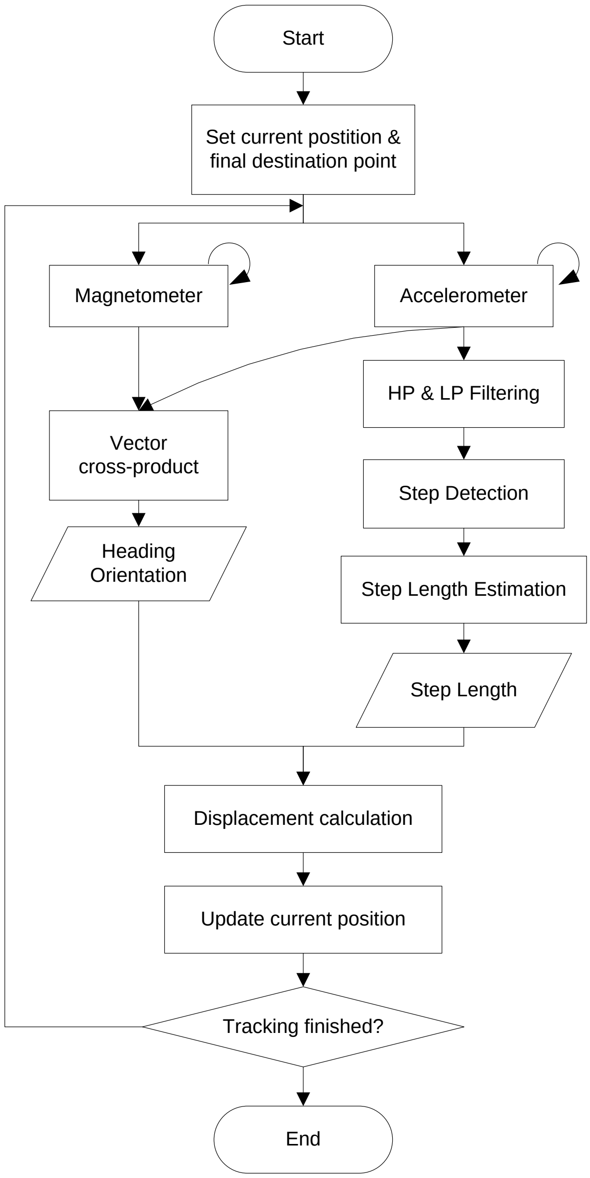

Fig. 2 Flowchart of system prototype

Fig. 2 shows that both magnetic field and acceleration data are used to obtain the heading orientation by vector cross product method. In addition, acceleration data is also used as a signal pattern to analyze step. The detail of each phase can be explained as follow:

1) *Filtering*

The raw acceleration signal must be filtered to obtain the desired output signal: gravity-free and noise-free signal. To eliminate the influence of gravity, the signal is filtered with high-pass filtering similar to [8]. The output of high-pass filtering then processed by low-pass filtering to smooth the signal and reducing random noise. Low-pass filtering has done by using a moving average filter, similar to [13]. The results of these filtration processes are gravity-free signal with minimalized noise, as shown in Fig. 3.

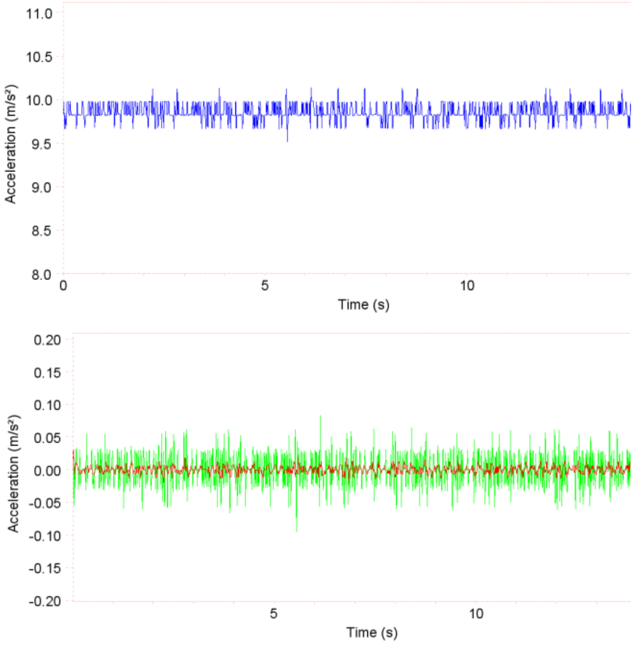

Fig. 3 Sample of accelerometer when smartphone was put flat on the table without moving in about 14 seconds. The upper plot depicts the magnitude of raw data. The lower plot, we perform High-pass filtering (green line) followed by Low-pass filtering (red line) of magnitude acceleration.

2) *Step Detection*

In order to detect foot steps, peak detection method was chosen. We detect two peaks: maxima as an impact of swing-phase; and minima as an impact of touch-down phase. Both maxima and minima must be detected in sequence in certain interval.

A maximum peak become a valid maxima if its acceleration value exceeds upper threshold. Upper threshold is calculated as the latest minima added by Δthreshold. In contrary, a minimum peak become a valid minima if its acceleration lower than lower threshold. Lower threshold is calculated as the latest maxima subtracted by Δthreshold, as equation (1). This scheme is known as relative threshold detection [3].

$$
\begin{aligned}
upper\_threshold_{step(k)} &= minima_{step(k-1)} - \Delta threshold \\
lower\_threshold_{step(k)} &= maxima_{step(k-1)} - \Delta threshold
\end{aligned} \tag{1}
$$

An universal approach was taken with initialization value of initial maxima, initial minima, and Δthreshold same to all subject tests. Initial maxima 1.32m/s², minima -1m/s², and Δthreshold 1.5 m/s² are determined experimentally.

3) *Step Length Estimation*

The displacement of user can be estimated through estimating step length whenever a valid step is detected. Our previous reseach [14] compares some estimation methods and shows that the best step length estimation method is Scarlet experimental method [10], as shown in equation (2). This method is able to give the closest estimation to actual distance compared to other three methods.

$$
step\_size = k \cdot \frac{\dfrac{\sum_{k=1}^{N} |a_k|}{N} - a_{\min}}{a_{\max} - a_{\min}} \tag{2}
$$

4) *Heading Orientation*

The user’s heading orientation is determined by magnetic azimuth that can be counted using gravity acceleration vector and geomagnetic vector. The vector cross product method is used to obtain magnetic azimuth. This method assumes that the navigation frame rotates with respect to the body frame and forms a new navigation frame [15]. Android already provides the implementation of this method, using getRotationMatrix in SensorManager.java class.

5) *Displacement Calculation*

The last phase after heading orientation and step length were obtained is displacement calculation. It projects the user displacement in vertical (y-axis) and horizontal (x-axis) component in cartesian coordinate, and then update the current position to the phone screen.

These phases are iteratively executed until tracking finished and sensor reading stopped.

B. *Experiment Scenario*

As mentioned before, this study is focused on performance testing of Indoor Tracking System utilizing only commonly integrated sensor on a smartphone without calibration process. The system prototype was developed on Android 4.1 Jelly Bean based, Samsung Galaxy SIII GT-I9300. The experiments were done in 3th floor hallway of the Department of Electrical Engineering and Information Technology building, Universitas Gadjah Mada with 30 test subjects who were asked to walk in normal speed in three different tracks:

Track 1: A – C – B with total distance about 51.54 m.

Track 2: A – C – D – E with total distance about 77.79 m.

Track 3: E – D – C – B with total distance about 82.67 m.

The floorplan of building is shown in Fig. 4.

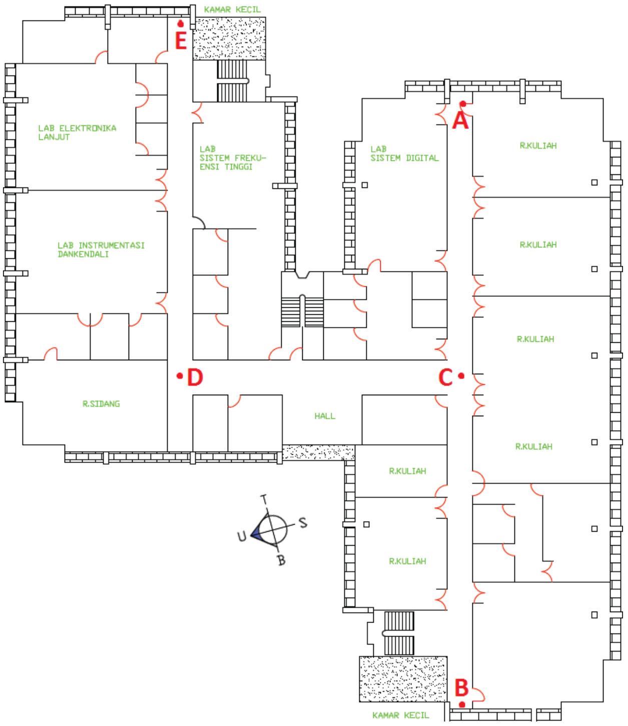

Fig. 4 Floorplan of Dept. of EEIT building

It was assumed that there were no obstacles in front of test subject while the test subjects walked, so they could walk in a straight way. Current position and destination point was determined before they starts moving. This is aimed to help the determination of ground-truth reference points. These reference points are useful to measure the error of estimated position, so the system performance could be known.

IV. Experiment Result

A. *Performance of Positioning System*

Performance of positioning system in this paper is measured from the accuracy of estimation points relative to the ground-truth points. The distance between estimation point and ground-truth point for whole steps then be averaged to obtain the average estimation error of a test subject. The ground-truth points are determined based on assumption that whole detected-steps have same length, so each step can be calculated as equation (3).

$$groundtruth\_steplength = \frac{total\ distance}{number\ of\ detected\ steps} \qquad (3)$$

Fig. 5 ilustrates estimation points and ground-truth points reference.

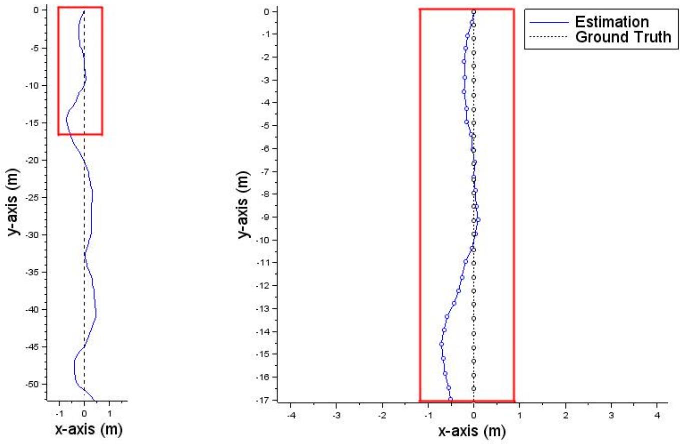

Fig. 5 Error estimation based on ground-truth points reference. Right side: the zoom view of the left side

The average estimation error of 30 test subjects on 3 different tracks can be show as follows:

1) *First track: A – C – B*

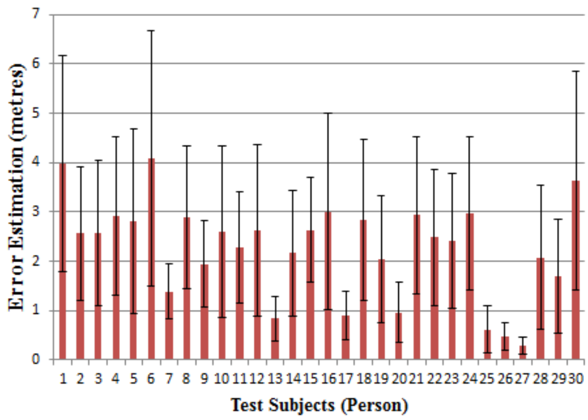

Fig. 6 Average error of whole test subjects in the first track

Fig. 6 shows that the biggest average error estimation was occured in test subject number 6, about 4.08 metres. The most accurate estimation was occured in test subject number 27, which only error about 0.29 metres. The average estimation error of all test subjects in track 1 is 2.25 metres.

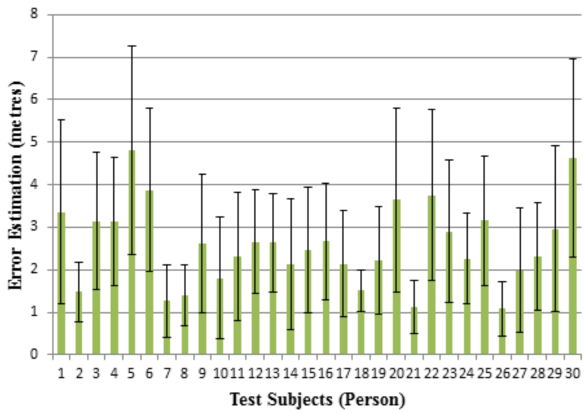

Fig. 7 Average error of whole test subjects in the second track

Fig. 7 shows that the biggest error estimation was occured in test subject number 5, about 4.81 metres.

The most accurate estimation was occured in test subject number 26, which only error about 1.08 metres. The average estimation error of all test subjects in track 1 is 2.58 metres.

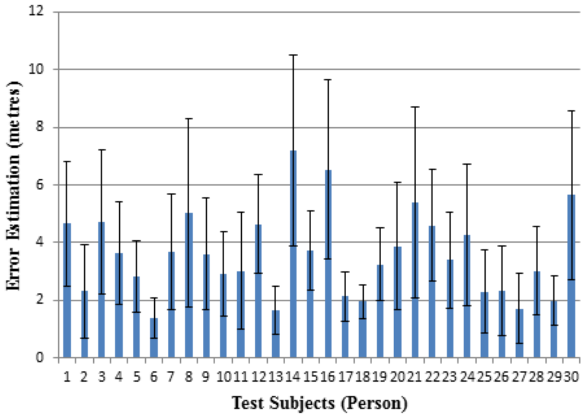

Fig. 8 Average error of whole test subjects in the third track

Fig. 8 shows that the biggest error estimation was occured in test subject number 14, about 7.20 metres. The most accurate estimation was occured in test subject number 6, which only error about 1.38 metres. The average estimation error of all test subjects in track 1 is 3.58 metres. The summary of overall average error is shown in Table 1.

TABLE I
AVERAGE ERROR OF OVERALL TRACKS

Track-	Total Distance (m)	Average Error (m)	Std.dev (m)	Max. Error (m)
1	51.54	2.25	0.99	4.08
2	77.79	2.58	0.96	4.81
3	82.67	3.58	1.47	7.20

Table I shows that the error has a trend to increase with increasing the total travelled distance. However, it can be compromised because this system only utilizing common sensors and used by 30 test subjects without calibration.

B. *Magnetic-field Fluctuation*

Our observation over all experiments data show that there was a skew heading orientation that happen in same place and same pattern, as shown in Fig. 9.

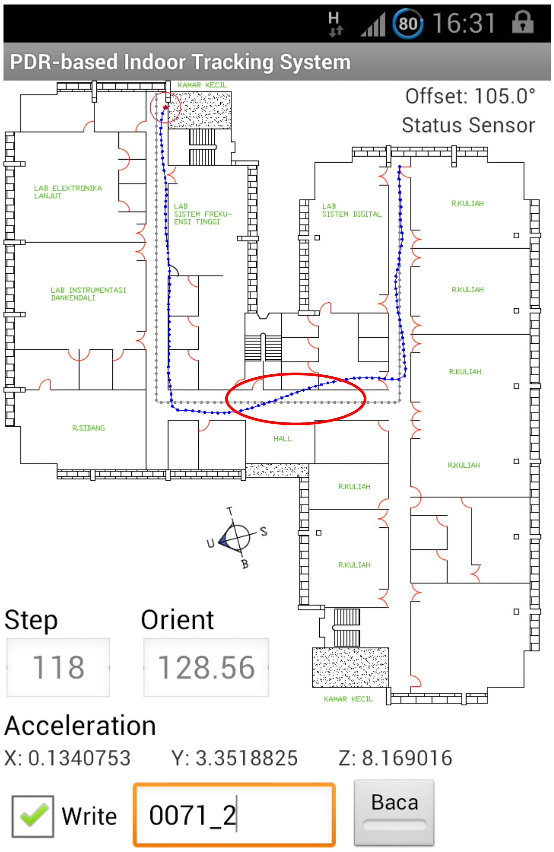

Fig. 9 Sample of a skew heading orientation on second track (A-C-D-E)

The skew heading orientation as shown in Fig. 9 was occured on whole test subjects who walk across that area. We can infer from this result that a magnetic field around that area has negatively influenced to the heading orientation. In addition, we observed magnetic field on side C to D using simple Android program that records the magnetic field. The result of magnetic field recording is shown in grayscale graph as shown in Fig. 10. The magnetic field is varying in range between 35 – 53 μTesla.

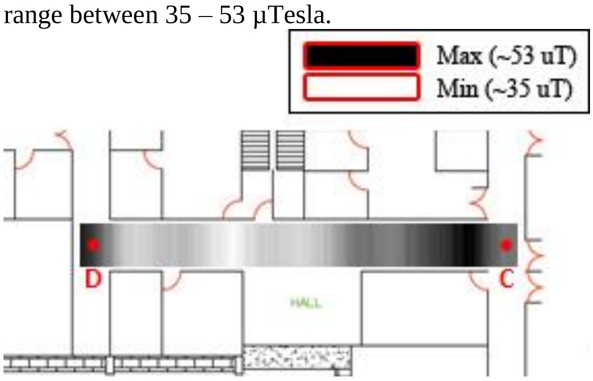

Fig. 10 Magnetic field fluctuation on grayscale graph

Fig. 10 represents maximum magnetic field with black color and minimum magnetic field with white color. The bigger magnetic field, the darker color appearance. In order to know the influences of these magnetic field, we observe the heading orientation on some points and the results is shown in Fig. 11.

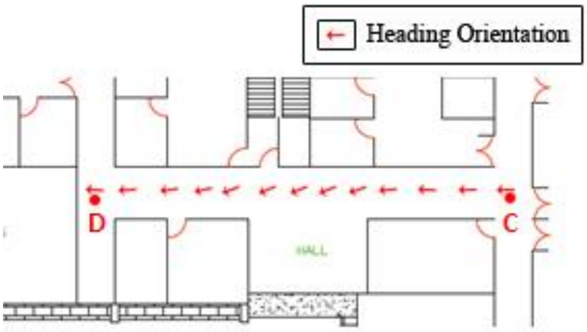

Fig. 11 Heading Orientation from side C to D

Fig. 11 shows that the weakened of magnetic field until below the normal (below 44μT) will influence heading orientation rotating counterclockwise. Another experiment in 2nd floor (it has same floorplan with 3rd floor) shows an identical pattern of skewed heading orientation, though it is not as extreme as in 3rd floor. Both 2nd and 3rd floor have same floorplan but they have different building structure because there are many windows in western wall of 2nd floor.

V. Conclusion

This paper presents performance testing of a positioning system with real-time Pedestrian Dead Reckoning method that can be used without calibration process. The performance testing is aimed to measure the accuracy of estimation position when the system is only equipped by accelerometer and magnetometer and used universally by 30 test subject in 3 different tracks.

The performance testing of positioning system was performed by measuring distance between estimation points and ground-truth points as truth reference. As increasing total travelled distance, the performance tends to decrease. In the first track (51.54m), average error estimation is 2.25m or 4.37% of total length. In the second track (77.79m), average error estimation is 2.58m or about 3.32% of total length. The last track (82.67m), average error of estimation is about 3.58m or 4.33% of total length.

Fluctuation of magnetic field on side C to D has negative effect to magnetometer when it determines the heading orientation. This fluctuation arises because of the building structure. However, it can be compromised because this system only using commonly-integrated sensor in smartphone which is targeted to be widely used by many people.

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