Smartphone-based Pedestrian Dead Reckoning as an Indoor Positioning System

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***Abstract*— Nowadays, personal positioning systems are more necessary to build many location-based services. Pedestrian Dead Reckoning (PDR), which is a pedestrian positioning technique using the accelerometer sensor to recognize pattern of steps, is an alternative method that has advantages in terms of infrastructure-independent. However, the variation of walking pattern on each individual will make some difficulties for the system to detect displacement. This is really interested authors to develop a sensor-based positioning system that applied generally to all individuals. In the test, 15 test subjects was taken with the distance of each 10m, 20m and 30m.**

Experiment begins with the feasibility test of accelerometer sensor. In this work, a smartphone with average sampling rate 63.79 Hz and standard deviation of 1.293 is used to records the acceleration. Then, the acceleration data are analyzed to detect step and to estimate the travelled distance using several methods. Detection of steps are able to make an average error of 2.925%, while the most nearly correct displacement estimation is using Scarlet experimental method which is make a distance average error of 1.39metres at all the traveled distance.

***Keywords*— pedestrian dead reckoning, sensor based positioning system, indoor positioning system, smartphone**

I. INTRODUCTION

Positioning is a technique that used to know object's position in a frame of reference. Generally, positioning can be done using some infrastructures-aid, such as Global Positioning System (GPS) satellite or Base Transceiver Station (BTS) cell-phone service provider. However, the implementation of indoor positioning system is still found any limitations, e.g GPS satellite signal dependence make this technique cannot be used in the building. Instead, positioning with BTS cell-phone can be used indoor seamlessly, but the accuracy is very small which is about 100 m up to 35 km [1]. Of course this limitations make them impossible to be implemented in indoor positioning.

Indoor positioning becomes important when user needs to know its position in a building, such as a firefighters who need to know about their position in a building during a rescuing effort. An alternative of indoor positioning is Pedestrian Dead Reckoning (PDR). PDR technique determines the latest position of a pedestrian by adding estimated displacement to starting known position. Displacement is represented by amount of steps and each step has its various step length. Detection number of steps and estimation of step length can be done using accelerometer sensor.

Recent smartphones which is coming with integrated accelerometer sensor become a new spirit to use PDR as a pedestrian indoor positioning system. This is because smartphones have small physical form and light in weight making easy to carry it anywhere. Moreover, using integrated-sensor in smartphone is less expensive than purchasing specialty hardware and it is more convenience in setting up the solutions to pedestrian. In this work, experimental data are collected with Samsung Galaxy SL with an Android simple program to record the acceleration.

The structure of this paper is as follows: Section II describes the principle of Pedestrian Dead Reckoning. This is then followed by our experimental scenario in Section III and our experimental results in Section IV. Finally, we conclude our work in Section V.

II. PEDESTRIAN DEAD RECKONING

Pedestrian Dead Reckoning (PDR) is a pedestrian positioning solution by adding distance travelled to the known starting position. Pedestrian distance travelled can be determined by using accelerometer sensor to detect steps and estimate displacement. Accelerometer sensor must be attached to the body to record the acceleration. Some related research has been done in previous studies using a special sensor modules that is attached on the helmet [2], attached at the foot [3],[4], or using low-cost sensor integrated in smartphone and placed it to the trouser pocket [5]–[7].

Basically, the implementation of PDR technique includes some operations: orientation projection, filtering, step detection, and step length estimation [5],[6]. However, this work is a subsystem of complete PDR system which is not include orientation projection process.

A. Orientation Projection

Accelerometer sensor actually indicates 3-axis acceleration relative to the smartphone itself. Therefore it can be projected from x,y,z local coordinate system to the world coordinate system to obtain the acceleration values in East-North-Up using magneticsensor. This process is usually used to resolve of smartphone arbitrary placement.

B. Filtering

The acceleration signal must be filtered to obtain the desired output signal: gravity-free and noise-free signal. Gravity is a low-frequency signal component that causing offset shift up the y-axis, about 9.8m/s². To eliminate the influence of gravity, the signal is filtered with high-pass filtering similar to [6], which is implemented with equation (1).

$$acc\_HPavg = acc\_new * (1-\alpha) + acc\_HPavg * \alpha;$$
$$acc\_HPfiltered = acc\_new - acc\_HPavg; \tag{1}$$

Low-frequency signal component, represented with mean of waveform, is subtracted to remove DC component. 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 as equation (2).

$$y[i] = \frac{1}{M} \cdot \sum_{j=-(M-1)/2}^{(M-1)/2} x(i+j) \tag{2}$$

where y[ ] and x[ ] are output average-filtered and input non-filtered signal. M is moving window, the number of points used in the moving average. In this paper, the value of M is taken as 5, which is obtained empirically through signal analysis.

Results of these filtration process are signal which is free from gravity and minimum random noise as shown in Fig. 1. Non-filtered signal represents with blue line, high-pass filtered signal represents with green line, while low-pass filtered signal represents with red line. The output of filtering process can be proceed further to obtain the information about the step occurence.

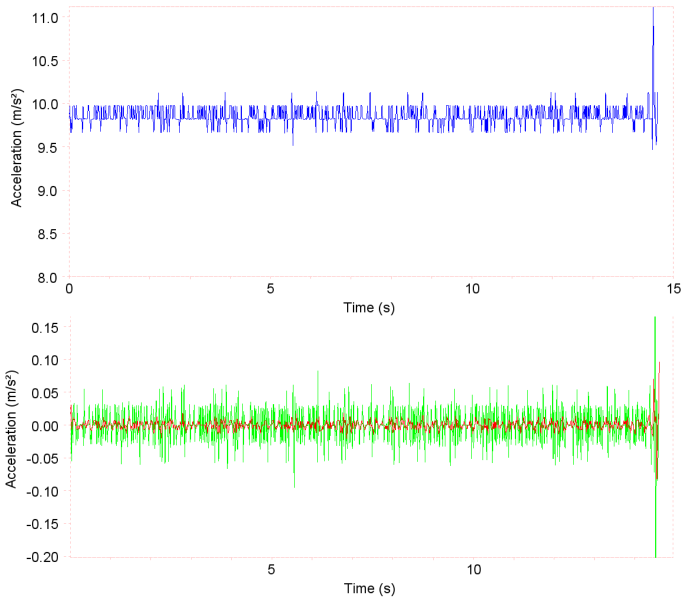

Fig. 1. Exemplary of accelerometer when smartphone was put flat on the table without moving in about 14 seconds. The upper plot depicts the magnitude of raw data. The lower plot, we perform High-pass filtering (green line) followed by Low-pass filtering (red line) of magnitude acceleration.

C. Step Detection

Pedestrian's distance travelled is represented by his/her step. Therefore, it is necessary to accurately detect step-occured in order to get better estimation. There are two common step detection methods which can be used to analyze acceleration signal: peak detection [4]–[6] and zero-crossing detection, [2],[7],[8].

The zero-crossing method counts signal crossing zero level to determine the occurence of step. Researchers usually have used time interval thresholding to reject false step detection. This method is not appropiate to detect user's steps in general-approached, because it requires certain time interval threshold to make decision whether the zero-crossing represents a valid step or not. The problem comes when time interval between footfalls varied for some subjects, so it is quite difficult to detect step accurately using zero-crossing method without calibration process.

The other method is to detect the peaks of acceleration. According to [4], the peaks of vertical acceleration correspond to the step occurences because the vertical acceleration is generated by vertical impact when the foot hits the ground. In this paper, we also use the peak detection method. However, we use magnitude of acceleration instead of vertical acceleration, in consider to resolve the problem of tilting. Because magnitude of acceleration will remain same whether the smartphone is tilted or not.

To detect step, we employ a relative threshold detection scheme similar to [5]. This scheme detects a step when valid maximum peak (as maxima) and valid minimum peak (as minima) are detected in sequence in a certain interval. Maxima is a maximum peak that exceeds upper threshold, while minima is a minimum peak that lower than lower threshold. The upper threshold is determined from summed last valid minima with a Δthreshold value, while the lower threshold is determined from subtracted last valid maxima with a Δthreshold value. In this paper, Δthreshold is a constant value that determined experimentally 1.8 for all test subjects. To ensure a valid step, an interval time difference between maxima and minima is also determined experimentally, must be between 120ms – 400ms.

D. Step Length Estimation

Total travelled distance can be calculated by estimating step length in every valid detected step. Generally, there are two methods for estimating step length: static method and dynamic method. Static method assumes that any valid steps having the same length, which can be determied through equation (3).

$$step\_size = height \cdot k \tag{3}$$

with k equal to 0.415 for men and 0.413 for women.

In contrary, dynamic method assumes any valid steps having their different step length which can be estimated using certain approaches, such as:

1) Weinberg approach, assume that vertical bounce, which is happen as a impact from walking activity, is proportional with step length [9]. The vertical bounce is calculated using peak-to-peak differences at each step as equation (4).

$$step\_size = k \cdot \sqrt[4]{a_{\max} - a}_{\min} \quad (4)$$

In this paper, k equal to 0.41 for all test subjects.

2) Scarlet approach: try to solve the accuracy problem caused by the variation in spring in the steps of different people, or in the steps of one person using different paces from one measurement to another [10]. This approach provides a simple solution that shows a correlation between the value of maximum, minimum, and average acceleration of the step length, as equation (5).

$$step\_size = k \cdot \frac{\frac{\sum_{k=1}^{N} |a_k|}{N} - a_{\min}}{a_{\max} - a_{\min}} \quad (5)$$

In this paper, k equal to 0.81 for all test subjects.

3) Kim approach, propose an experimental equation as (6) which is representing a relation between step length and average acceleration which occur during a step [4]. Constant value k is modified due to different placement of sensor. In this paper, k sets to 0.55.

$$step\_size = k \cdot \sqrt[3]{\frac{\sum_{k=1}^{N} |a_k|}{N}} \quad (6)$$

III. EXPERIMENTAL SCENARIO

In order to evaluate the reliability of system to detect displacement in the variation of walking pattern without calibration, the actual walking test was done. We chose 15 test subjects consist of eight males and seven females in aged ± 20 years old. The height of the test subjects ranged from 1.55m to 1.75m. For each person, three recordings were done at the normal walking rate of the person in various known distance: 10m, 20m, and 30m. The experiments were done in 3th floor hallway of the Department of Electrical Engineering and Information Technology building, Gadjah Mada University, Indonesia. We used an accelerometer sensor integrated in Samsung Galaxy SL I9003 with Android Gingerbread operating system. The acceleration value then proceed in Scilab with procedure as shown in flowchart in Fig. 2. In experiments, smartphone was placed in the hand, as shown in Fig.3, and it was assumed that no obstacles in front of subject.

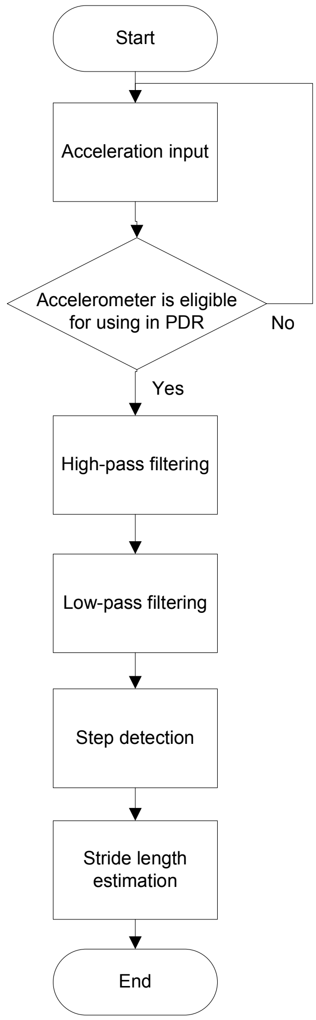

Fig. 2. Flow chart of overall the positioning system

Fig. 3. Experimental scenario. Smartphone was placed in the hand as using phone normally while user walks in straight path

IV. Experimental Result

A. Eligibility of Smartphone Sensor

Eligibility of a sensor is observed from the sampling frequency and standard deviation. Sampling frequency shows how fast a sensor sampling the data, while standard deviation indicates the sensor stability in keeping sampling interval.

From several tests, our accelerometer has a sampling rate about 63.78831Hz. It indicates that this sensor has quite high frequency sampling compared to smartphone Google Nexus One and HTC Hero in [5] which only have sampling rate not more than 25 Hz. Standard deviation value quite close to zero, at 1.293, shows that values of the data population is close to its average value.

B. Step Detection

In order to detect a valid step, we implement a relative threshold as explained in Section 2. Fig. 4 illustrates three valid steps taken from a walking pattern of a test subject. Blue dot points represent a valid maxima which is a peak acceleration exceeding upper threshold. Black dot points represent minima which is peak acceleration lower than lower threshold. Upper threshold is shown in the blue dashed-line, while lower threshold is shown in black dashed-line. A step is detected when valid maxima and minima are detected in sequence in a certain interval.

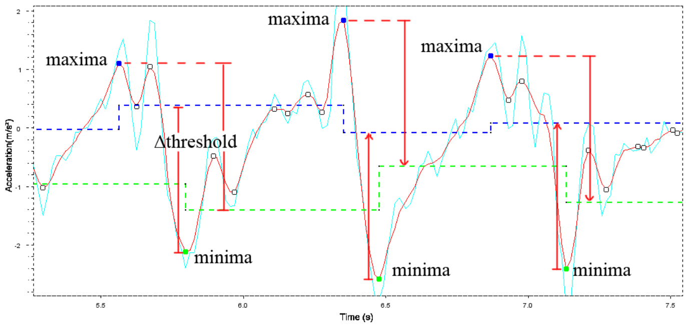

Fig. 4. Three steps walking pattern of a subject are detected with relative threshold scheme

This scheme is implemented to whole test subjects without individual calibration process to fit their walking pattern. To compare the error from different distance, we use percentage error which is calculated from difference of actual steps counted and steps detected.

1) 10m travelled distance

In the shortest path, 10 metres travelled distance, entire test subjects take varies number of steps, between 15 to 20 steps. The average taken step is 17 with standard deviation of 1.464. The average error percentage for 10 metres distance is 4.16% with standard deviation of 5.34. The error over all test subjects is shown in Fig. 5.

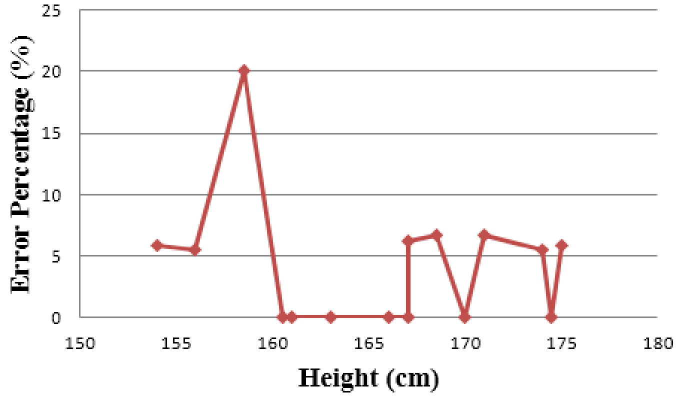

Fig. 5. Error percentage of step detection in 10m travelled distance

Fig. 5 shows that there are seven test subjects whose their steps can be detected without error. Moreover, there is only one subject which have extreme error 20%. Fig. 6 and Fig. 7 show the acceleration of walking pattern recorded from different subject when they asked to walk for 10m straight path.

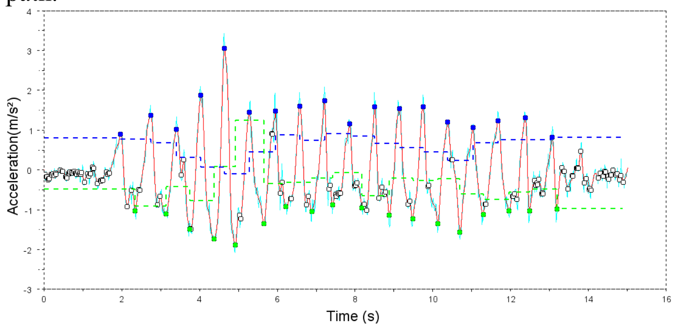

Fig. 6. The acceleration of 10m length walking pattern recorded from test subject number 14. This is an example which all steps can be detected without error

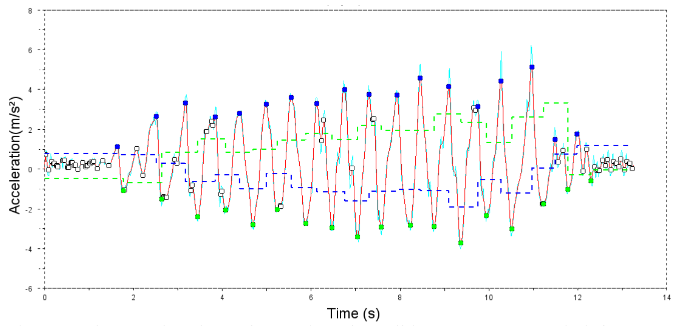

Fig. 7. The acceleration of 10m length walking pattern recorded from test subject number 6

Fig. 6 shows walking pattern of test subject number 14. She took 18 steps when she walked 10metres path. Our system can detect all her steps without an error. Fig. 7 shows walking pattern of test subject number 6 which has extreme error 20%. This subject is a female with 158.5cm height. Our system has over detecting her step to 18 steps which actually she only took 15 steps. In this case, over detecting is caused by Δthreshold which is too low for this test subject. She has quite high average peak-to-peak acceleration, about 6.249. Hence, there is three steps-like pattern detected as valid steps.

2) 20m travelled distance

In the experiments at distance of 20 metres, the entire test subjects take a number of steps, varies between 28 to 36 steps. The average of taken step is 32 steps with standard deviation of 2.02. The error percentage of 20 metres travelled distance shown in Fig. 8.

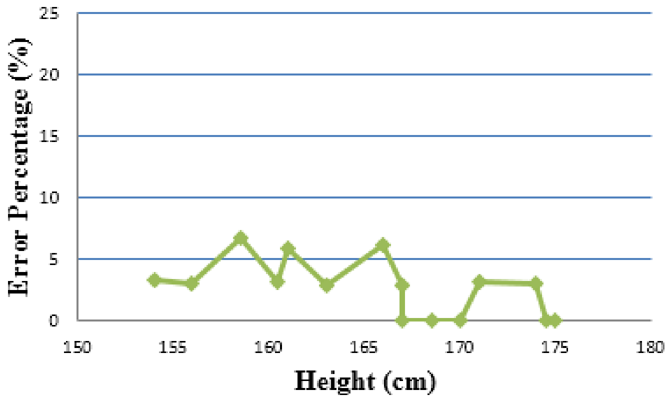

Fig. 8. Error percentage of step detection in 20m travelled distance

Fig. 8 shows that there are only three test subjects which have error percentage over 5%. The average error is 2,65% with standard deviation of 2.31. There is no extreme error from test subject number 6 in this distance. So far, we can infer from this results that step detection in 20 meters is better than 10 meters.

3) 30m travelled distance

In the experiments at the longest path, 30 metres travelled distance, the entire test subjects also take a number of steps, varies between 43 to 53 steps. The average of taken step is 47 steps with standard deviation of 2.77. The error percentage of all subjects is shown in the Fig. 9.

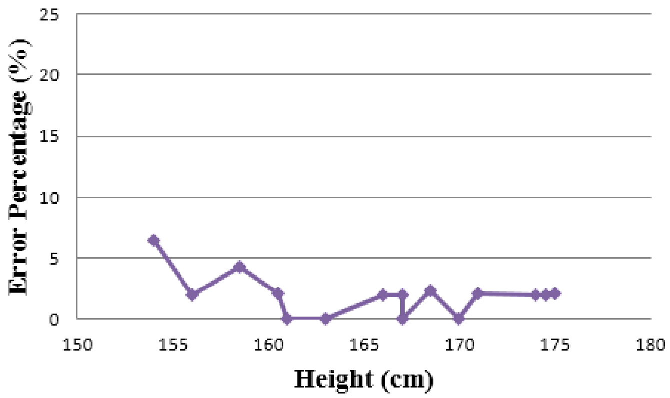

Fig. 9. Error percentage of step detection in 30m travelled distance

Fig. 9 shows that only one subject which has an error percentage over 5%. The average error is 1.97 with standard deviation of 1.725.The overall results of step detection error can be seen in figure 10.

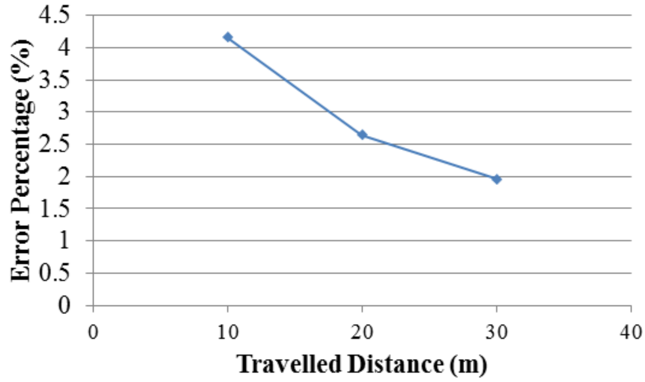

Fig. 10. The overall results of step detection error percentage

We can infer from this result that longer travelled distance resulting in fewer error percentage and vice versa. These results verify that the peak detection algorithm is able to detect steps in regular walking pattern. The irregular walking pattern (e.g initial acceleration in the beginning of motion and stopping acceleration in the end of motion) is more difficult to detect steps robustly. Hence, longer travelled distance resulting in fewer error percentage because it can be more normalized.

However, average error percentage in all traveled distances are only about 2.925%. It shows that the method is quite reliable in detecting steps without performing individual calibration process.

C. Travelled Distance Estimation

As explained in Section 2, total travelled distance can be calculated by estimating step length in every valid detected step. We use a static method and three dynamic methods, as equation (3), (4), (5), and (6), to estimate the step length. Comparison of total travelled distance using these methods is shown in figure 11.

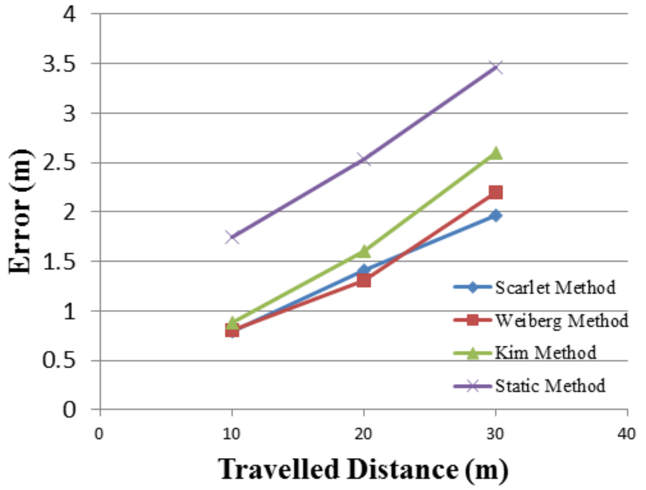

Fig. 11. Travelled distance estimation error

Figure 11 shows that the overall methods produce error estimation which have a trend to increase with increasing travelled distance. However, dynamic methods, which is representing in Scarlet, Weinberg, and Kim method, produce a smaller error compared to static method.

Table 1 shows the estimation error for each method.

TABLE 1
DISPLACEMENT ESTIMATION ERROR

Method	**Displacement Estimation Error**	
	Average (metres)	**Std. Deviation**
Static	2.5815	1.5859
Kim	1.6917	1.2858
Weinberg	1.4357	1.1896
Scarlet	1.3913	1.1675

Table 1 shows that the Scarlet method can estimate travelled distance better than the other methods. This is indicated by the smallest average estimation error and the smallest standard deviation.

V. CONCLUSION

This paper presents a positioning system that can be used generally to 15 test subjects without the individual calibration process. The system focused on displacement estimation by utilizing the accelerometer sensor integrated on a smartphone which is placed in the hand.

Step detection on various walking pattern without calibration process results an average error of 2.925%. This result shows that step detection using relative-threshold peak-detection is quite reliable to detect steps of all test subjects with general-approached. When a step detected, step length should be determined to estimate displacement. In this work, step length estimation performed using a static method and three dynamic methods. The three dynamic methods give better displacement estimation than static method. The best dynamic method is Scarlet experimental method which is giving the closest estimation to actual distance.

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