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***Research paper***

# Distance measurement using proximity sensor in pedestrian and bicycle navigation

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**Abstract**

Navigation plays an important role in life where it has applications in many disciplines such as transportation services and infrastructure maintenance. Navigation applications depend on reliable, trustful and continuous navigation solution that overcomes the Global Navigation Satellite System (GNSS) denied environments. To achieve this issue, GNSS is now commonly used with other navigation systems such as Inertial Navigation System (INS). Pedestrian dead reckoning usually uses the resultant of 3-axes accelerometer values for step detection; the randomness of the pedestrian hand-held habit the step detection cannot always be accurate by using the accelerometer sensor data. Furthermore, the signal trend of the accelerometer could differ significantly due to the carrying modes and the user's hand high dynamics. This paper represents a new idea for distance measurement during dead reckoning navigation depending on the proximity sensor which attached to most smartphones to lock screen while making calls for power saving. The new idea summarized in using the proximity sensor for steps counting in case of pedestrian dead reckoning (PDR) or cycles counting in case of bicycle dead reckoning (CDR).
In PDR the distance measurement is depending on counting number of steps and knowing the stride length of user which is variable from person to other, so a least square models have been constructed to estimate the stride length of person depending on his height, weight ,age and gender.
Although stride length estimation for users but the PDR has a less accuracy comparing with CDR where the stride length can be changed while walking and cannot be controlled like cycle length.
The experiments proved that the proximity sensor is a good tool in detecting number of steps and cycles in PDR and CDR respectively, the bicycle mode gives more accurate results in distance measurements compared with walking mode where the average error in case of PDR= 2 % and in case of CDR=0.53 % .

***Keywords***: *Dead Reckoning Navigation; Step Counting; Cycle Counting; Proximity Sensor; PDR and CDR.*

## 1. Introduction

Nowadays; smartphones are in use all over the world, mainly for voice, visual and data communications. Most smartphones contain inertial sensors consist of accelerometers, gyroscopes and magnetometers. Inertial sensors have been used in various applications, such as navigation, robotics, etc. The rapid development of Micro-Electro-Mechanical Systems (MEMS) has opened the mind for creativity of new applications, such as human activity monitoring, fall detection, and medical treatment [1].
Pedestrian dead reckoning (PDR) application depends on measuring the travelled distance from the known position to the unknown one; In addition to measure the orientation between them. The travelled distance can be simply calculated by multiplying the number of steps by the stride length of person, so the algorithm of PDR mainly depends on step detection and counter. Based on the physiological attributes of the pedestrian, the waveform for the resultant of 3-axis accelerometer values can be obtained for the formation of cyclical changes. Therefore, the cyclical and attributes values can be used for step detection [2].
Actually, due to the randomness of the pedestrian hand-held habit the step detection cannot always be accurate by using the accelerometer sensor data. Furthermore, the signal trend of the accelerometer could differ significantly due to the carrying modes and the user's hand high dynamics. Hence, there are many precautions have to be taken into consideration to get high-accurate measurements by using an accelerometer which is mounted on a Smartphone. Accordingly, such method is not always efficient in navigation applications. However, it is suitable for healthy application, where people wanting to increase their physical activity (people, especially suffering from obesity) [3-4].
There are many previous researches in area of step counting such as [5] proposed a new algorithm can discard irrelevant motion and count user's steps accurately. The overall classification accuracy is 89.4%. Accelerometer, gyroscope and magnetic field sensors are used in the device. [6] Developed a step counter algorithm depending on zero crossing scheme and liner regression. The paper reported 90.63% accuracy. Another study by [7] reaches 91.5% accuracy using an arm mounted, commercial and advanced physiological signal measurement device and machine learning techniques. [8] Tested a new algorithm for of six different placements of smartphone. The obtained accuracy of step counting is greater than 97% using standard deviation thresholding and windowed peak detection. [9] Developed a new step counter algorithm using IMU and magnetometer. The proposed algorithm achieves more than 99 % accuracy. [10] proposed a novel algorithm to simultaneously detect

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walking motion and count steps through unconstrained smartphones in the sense that the smartphone placement is not only arbitrary but also alterable. The main idea of algorithm depending on extracting the frequency domain features from three-dimensional (3D) angular velocities of a smartphone through FFT (fast Fourier transform).the paper showed that the accuracy of step counting reaches to 95.74 % . This accuracy can be transformed into distance accuracy by means of stride length.

Beside the inertial sensors equipped in most smart phones, there are other sensors such as camera and barometer and proximity sensor (PS), The proximity sensor is usually used to determine how far away a person's head is from the face of a handset device (for example, when a user is making or receiving a phone call). Most proximity sensors return the absolute distance in cm. In our scope of work an external (PS) was used as a detector for the number of steps in (walking mode) and as a detector for the number of cycles in (bicycle mode).

## 2. Methodology

A new hardware system was aggregated which consist of proximity sensor (a) ,Arduino USB board (b), micro SD card module (c), and 9-volt battery (d) as shown in (Fig. 1)

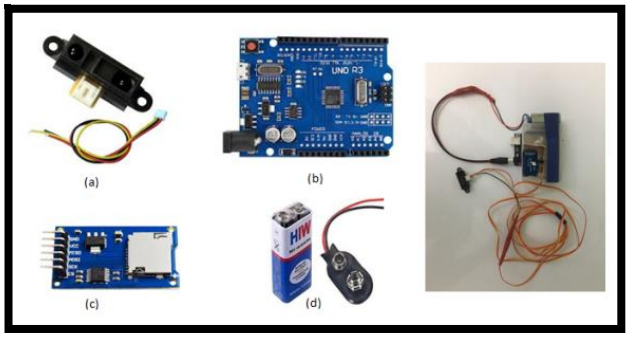



**Fig. 1:** Components of New Hardware System.

### 2.1. Step detection

In order to step detection while walking mode, a PS is fixed on one of two feet of a person, making its face is as close as possible to ground to ensure that the (PS) will correctly work., as shown in (Fig. 2).



**Fig. 2:** PS Attached to Foot Of User.

During the walking mode, the PS will visit the ground by a number equals to half of the number of steps of walking since the sensor attached to only one foot. The step will be sensed when the (PS) will face the ground where the (PS) will record (zero=off) and will be recorded as a step, otherwise it will record the maximum range in cm (on) that can be detected by (PS).

Logically, between every two successive steps sensed by the attached (PS) to foot, there is one step from other free one. Hence, the steps done by free foot can be predicted, and getting a total number of steps through the travelled path. (Fig. 3) presents a sample of (PS) readings with counted (sensed) steps and predicted steps.

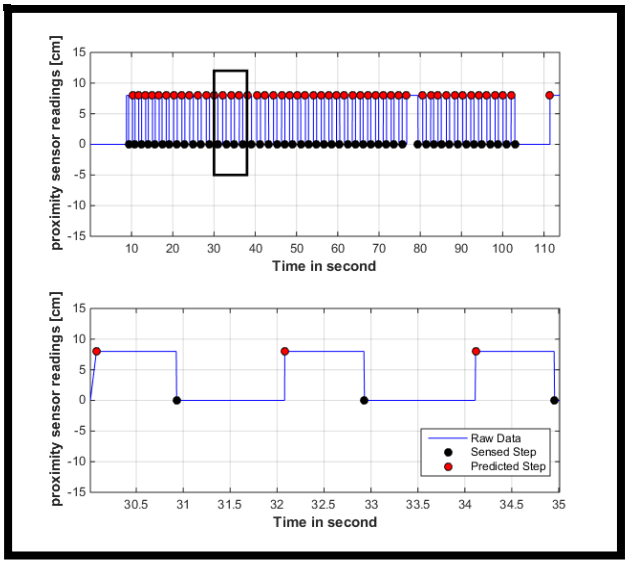



**Fig. 3:** Raw Data from Proximity Sensor and the Counted Steps.

To check the efficiency of PS in step detection, the PS was attached to feet of users and they counted them steps and comparing to the automatically counted by PS. The experiments proved the high accuracy of step counting using PS. the obtained accuracy ranges from 99 % up to 100 % with average value of 99.84% (Table 1). The accuracy is not depending on the user characteristics where the threshold concept does not used in step detection.

**Table 1:** Experiments of Step Counting Using PS

| Exp.# | Counted steps | True steps | Accuracy % |
|---|---|---|---|
| 1 | 13 | 13 | 100 |
| 2 | 62 | 62 | 100 |
| 3 | 100 | 100 | 100 |
| 4 | 260 | 260 | 100 |
| 5 | 301 | 300 | 99.7 |
| 6 | 410 | 414 | 99.03 |
| 7 | 500 | 500 | 100 |
| 8 | 1000 | 1000 | 100 |

### 2.2. Stride length modeling

After a step is counted, the next stage for the PDR is to determine the estimated stride length for a user. Biomechanical studies have shown that usually, the user's stride length is proportional to the length of the user's leg and subsequently to the user's height [11]. A new stride length model for user had been designed, in this work, and empirically validated by adding new affecting factors such as weight, age and gender of users.

To build a stride length model, the number of steps done through walking on a pre-calibrated path was collected for 45 users varying in age, height, weight, and gender. (Fig. 4) shows the relation between every factor with the stride length of person. The correlation coefficient (R) reaches to 0.79 depending on users' heights and 0.44 depending on their weights and -0.12 in case of Ages, Also males usually have longer stride length compared with females.

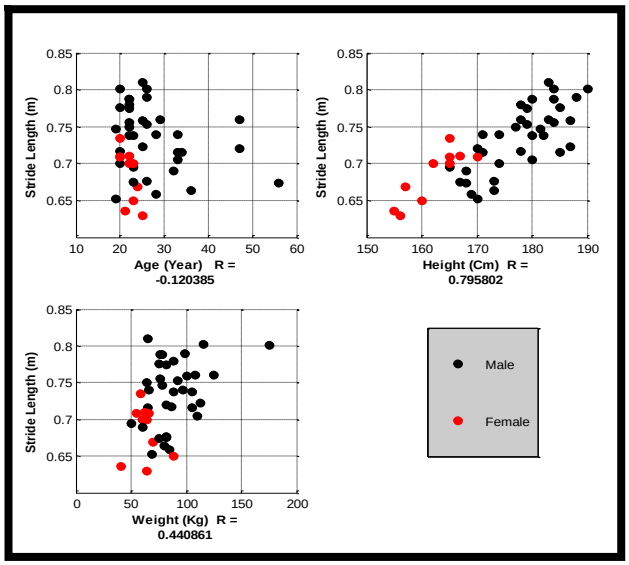



**Fig. 4:** Correlation between Stride Lengths of Users and their Age, Height, Weight and Gender.

### 2.2.1. Least square adjustment (LSA)

A Combined least squares adjustment has been used to fit the input data of users (age, height and weight) and the output (stride length) to represent an empirical equation.

$$SL_m - (a * A_{year}) - (b * H_{cm}) - (c * W_{kg}) = 0 \quad (1)$$

Where:
A, b and c: are the parameters.
$SL$ : is the Stride length of user in meters.
$A$ : is the Age of user in years.
$H$ : is the Height of user in cm.
$W$ : is the Weight of user in Kg.
The parameters have been calculated and have the following values in case of males

**Table 2:** Parameters of Stride Length Computation (Male)

| parameter | value |
|---|---|
| $a$ | $-4.889 * 10^{-4}$ |
| $b$ | $4.3 * 10^{-3}$ |
| $c$ | $-1.161 * 10^{-4}$ |

(Fig. 5) shows the efficiency of the model where it represents the relation between the observed stride lengths of users (true) and the modeled one from the previous equation, the average error is 3.4% and the root mean square error equals ±2.9 cm.

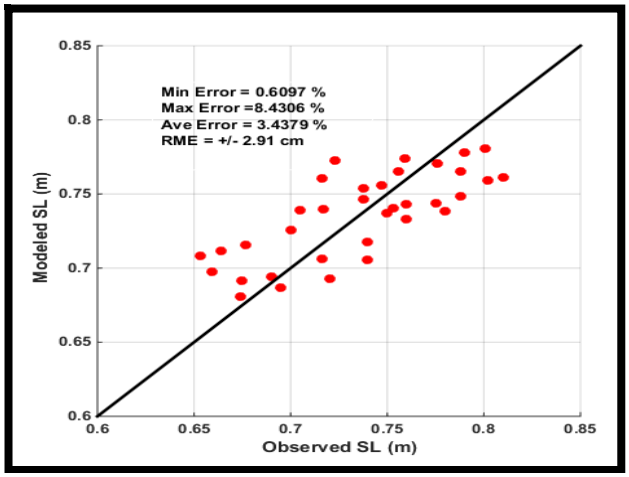



**Fig. 5:** Relation between the Actual Stride Lengths and the Modeled Ones by Least Square Adjustment (Males).

Another model was constructed for females and the parameters have the following values

**Table 3:** Parameters of Stride Length Computation (Female)

| parameter | value |
|---|---|
| $a$ | $-4.3 * 10^{-3}$ |
| $b$ | $4.9 * 10^{-3}$ |
| $c$ | $-2.21 * 10^{-4}$ |

(Fig. 6) represents the efficiency of female model where it shows the relation between the observed stride lengths of users (true) and the modeled one from the previous equation, the average error is 2.05% and the root mean square error equals ± 1.65 cm.

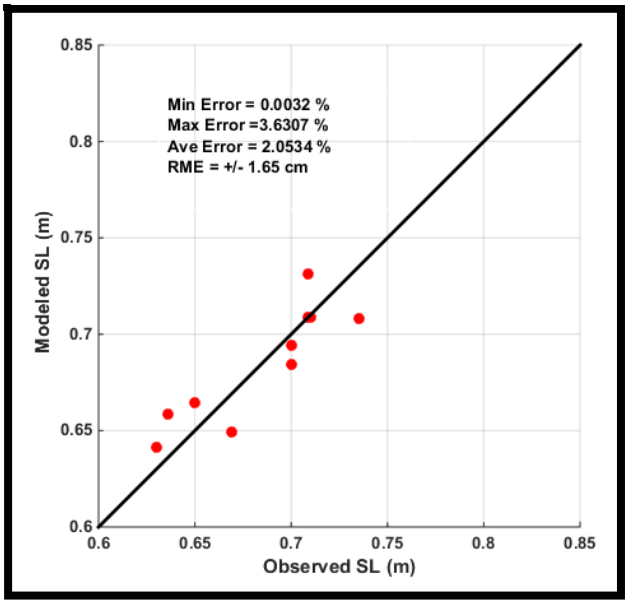



**Fig. 6:** Relation between the Actual Stride Lengths and the Modeled Ones by Least Square Adjustment (Females).

## 2.3. Cycle detection

The PS was fixed in bike as close as possible to one of wheels of bike; four-wheel signal tires were attached to the same wheel. Finally when the bike is moving, the PS will be fixed and the wheel signal tires only will spin.



**Fig. 7:** The PS Attached To Bicycle and Four Wheel Tire Signals Attached to Wheel.

During the bicycle mode, the wheel signal tires will visit the fixed PS by number equals to four times number of cycles done by wheel. The quarter cycle will be sensed when every wheel signal tire faced to the (PS), the (PS) will read (zero=off) and will be recorded as a count otherwise will read its maximum range in cm (on).

The travelled distance can be calculated by multiplying the number of cycles by the outer perimeter of wheel as:

$$L = \frac{NC}{4} * 2 * \pi * \quad (2)$$

Where:
$NC$: is the number of counts.
$r$: is the radius of bicycle wheel.
(Fig. 8) shows the counts of sensor (black spots) through the journey and those black spots sometimes are converged and sometimes are diverged. This means that the velocity of bicycle was variable and can be calculated at any time of journey.
It is clear that the error is a function in wheel radius where the larger the radius, the greater the error. The purpose of using four wheel signal tires is to be measuring the distance with accuracy equals 0.25 cycle in ideal case when there are no errors from user or other sources of errors.

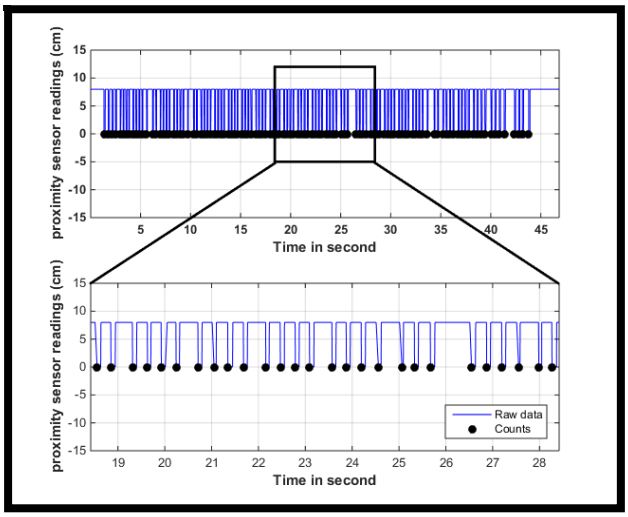



**Fig. 8:** Raw Data from Proximity Sensor and Its Counts (Bicycle Mode)

## 3. Experiments and result

Walking mode
In a walking mode, the created hardware system was used in data collection and four pre-calibrated paths measured by total station and tested by group of users. (Table 4 & 5) show the results for each path and percentage of error

$$\%\ Error = \frac{|Measured\ distance - Calculated\ distance|}{Measured\ distance} * 100$$

**Table 4:** Four Tested Paths by Group of Users (Male)

| | User (male) | | | | | | | | |
|---|---|---|---|---|---|---|---|---|---|
| | 1 | 2 | 3 | 4 | 5 | 6 | 7 | 8 | 9 |
| Age (year) | 26 | 26 | 28 | 36 | 26 | 28 | 25 | 29 | 26 |
| Height (Cm) | 165 | 173 | 173 | 173 | 179 | 180 | 182 | 184 | 187 |
| Weight (Kg) | 65 | 84 | 94 | 80 | 92 | 84 | 63 | 93 | 97 |
| SL (m) (modeled) | 0.689 | 0.721 | 0.719 | 0.717 | 0.746 | 0.751 | 0.763 | 0.766 | 0.780 |
| | Path No 1 ( 30.472 m ) (Measured by total station) | | | | | | | | |
| $N_{Counted\ Steps}$ | 45 | 43 | 42 | 43 | 41 | 43 | 40 | 40 | 39 |
| Length (m) | 31.005 | 31.003 | 30.198 | 30.831 | 30.586 | 32.293 | 30.520 | 30.640 | 30.420 |
| * %Error | 1.75 | 1.74 | 0.9 | 1.18 | 0.37 | 5.98 | 0.16 | 0.55 | 0.17 |
| | Path No 2 ( 59.131 m ) (Measured by total station) | | | | | | | | |
| $N_{Counted\ Steps}$ | 86 | 86 | 82 | 82 | 80 | 87 | 77 | 75 | 77 |
| Length (m) | 59.254 | 62.006 | 58.958 | 58.794 | 59.680 | 65.337 | 58.751 | 57.450 | 60.060 |
| * %Error | 0.208 | 4.862 | 0.293 | 0.570 | 0.928 | 10.495 | 0.643 | 2.843 | 1.571 |
| | Path No 3 ( 96.641 m ) (Measured by total station) | | | | | | | | |
| $N_{Counted\ Steps}$ | 145 | 136 | 134 | 140 | 130 | 143 | 125 | 125 | 126 |
| Length (m) | 99.905 | 98.056 | 96.346 | 100.38 | 96.980 | 107.39 | 95.375 | 95.750 | 98.280 |
| * %Error | 3.377 | 1.464 | 0.305 | 3.869 | 0.351 | 11.126 | 1.310 | 0.922 | 1.696 |
| | Path No 4 ( 137.21 m ) (Measured by total station) | | | | | | | | |
| $N_{Counted\ Steps}$ | 205 | 190 | 180 | 195 | 187 | 193 | 177 | 175 | 174 |
| Length (m) | 141.24 | 136.99 | 129.42 | 139.81 | 139.50 | 144.94 | 135.05 | 134.05 | 135.72 |
| * %Error | 2.941 | 0.160 | 5.677 | 1.899 | 1.670 | 5.636 | 1.574 | 2.303 | 1.086 |

**Table 5:** Four Tested Paths by Group of Users (Female)

| | User (female) | | | | | | |
|---|---|---|---|---|---|---|---|
| | 1 | 2 | 3 | 4 | 5 | 6 | 7 |
| Age (year) | 19 | 21 | 19 | 20 | 26 | 25 | 19 |
| Height (Cm) | 166 | 162 | 160 | 160 | 158 | 160 | 164 |
| Weight (Kg) | 65 | 92 | 59 | 55 | 51 | 55 | 46 |
| SL (m) (modeled) | 0.717 | 0.683 | 0.689 | 0.686 | 0.651 | 0.664 | 0.712 |
| | Path No 1 ( 30.472 m ) (Measured by total station) | | | | | | |
| $N_{Counted\ Steps}$ | 43 | 44 | 48 | 45 | 47 | 45 | 44 |
| Length (m) | 30.845 | 30.059 | 33.085 | 30.863 | 30.603 | 29.896 | 31.316 |
| * %Error | 1.224 | 1.355 | 8.575 | 1.283 | 0.430 | 1.890 | 2.770 |
| | Path No 2 ( 59.131 m ) (Measured by total station) | | | | | | |
| $N_{Counted\ Steps}$ | 84 | 85 | 93 | 86 | 92 | 88 | 84 |
| Length (m) | 60.256 | 58.069 | 64.101 | 58.983 | 59.904 | 58.462 | 59.786 |
| * %Error | 1.903 | 1.796 | 8.405 | 0.250 | 1.307 | 1.131 | 1.108 |
| | Path No 3 ( 96.641 m ) (Measured by total station) | | | | | | |
| $N_{Counted\ Steps}$ | 133 | 139 | 146 | 138 | 149 | 142 | 136 |
| Length (m) | 95.406 | 94.960 | 100.63 | 94.647 | 97.018 | 94.337 | 96.796 |
| * %Error | 1.278 | 1.739 | 4.130 | 2.063 | 0.390 | 2.384 | 0.160 |

| | Path No 4 ( 137.21 m ) (Measured by total station) | | | | | | |
|---|---|---|---|---|---|---|---|
| $N_{Counted\ Steps}$ | 187 | 196 | 208 | 197 | 211 | 202 | 195 |
| Length (m) | 134.142 | 133.901 | 143.366 | 135.111 | 137.388 | 134.198 | 138.788 |
| * %Error | 2.236 | 2.412 | 4.487 | 1.530 | 0.130 | 2.195 | 1.150 |

From previous tables, it is obvious that there is random error in results where the error for every user not constant in every path. These errors usually are personal errors due to change in the stride length of user while walking especially when the path goes longer. The average error for all paths and users in previous tables was calculated as a weighted mean relative to each path length (d) where the shortest path has a big weight and vice versa, The final average error from next equation=2%.

$$Weighted\ mean\ Error\ = \frac{\sum_{i=1}^{i=n} p_i * \sigma_i}{\sum_{i=1}^{i=n} p} \quad (3)$$

Where:

$p_i$ : is the weight, $p_i \propto \frac{1}{d}$

$\sigma_i$ : is the error

N: is the number of users * number of paths

### 3.1. Bicycle mode

In a bike mode, the created hardware system and a bicycle its wheel radius 0.33 m used in data collection and the same previous paths were tested.

**Table 6:** Four Paths Tested Three Times with Variable Speeds

| | | | | |
|---|---|---|---|---|
| | Path No 1 ( 30.472 m ) (Measured by total station) = (14.72 Cycle) | | | |
| $N_{Counted\ Cycles}$ | 15 | 14.75 | 13.75 | Weighted mean = 14.58 ± 0.3 Cycle |
| Average Speed (km/h) | 4.3 | 4.6 | 6.18 | % Error = 0.95 |
| | Path No 2 (59.131 m) (Measured by total station) = (28.56 Cycle) | | | |
| $N_{Counted\ Cycles}$ | 29.25 | 28 | 28.75 | Weighted mean = 28.66 ± 0.02 Cycle |
| Average Speed (km/h) | 4.49 | 4.77 | 9.81 | % Error = 0.35 |
| | Path No 3 (96.641 m) (Measured by total station) = (46.6 Cycle) | | | |
| $N_{Counted\ Cycles}$ | 46.5 | 46.25 | 47.75 | Weighted mean = 46.61 ± 0.33 Cycle |
| Average Speed (km/h) | 4.89 | 4.68 | 11.61 | % Error = 0.02 |
| | Path No 4 (137.21 m) (Measured by total station)= (66.28 Cycle) | | | |
| $N_{Counted\ Cycles}$ | 67 | 67.25 | 65.75 | Weighted mean = 66.82 ± 0.36 Cycle |
| Average Speed (km/h) | 5.06 | 4.18 | 7.81 | % Error = 0.81 |

$$\%\ Error = \frac{|measured - Weighted\ mean|}{measured} * 100$$

From (Table 6), it is obvious that there is random error in result where the number of counted cycles for every path not constant in every time. The errors usually are personal errors due to miss starting and ending at the marked start and end of path and due to speed increase. The average length in every path was calculated as a weighted mean relative to each speed where the path with low speed has a big weight and vice versa. Finally; the average error from all paths = 0.53%.

## 4. Conclusions

The paper gives a novel hardware for step and cycle counting, the experiments proved the efficiency of proximity sensor in detecting number of steps and cycles in PDR and CDR respectively, the bicycle mode gives more accurate results in distance measurements comparing with walking mode where the average error in case of PDR= 2 % and in case of CDR=0.53 % because of no changing in cycle length which depending only on radius of bicycle wheel; on the contrary in stride length which changing from person to other and also changing for one user while the same journey depending on his/her speed.

It's recommended in PDR to update the position of user every 50 meters and reset the proximity sensor to maintain the previous accuracy which is almost 1 m , and in CDR every 100 meters to reach almost 0.5 m accuracy.

Finally; although existence of error in the presented method but all error is acceptable in field of navigation where the target is how to know your position with few meter accuracy specially in GPS denied environments, such Unplanned area ,narrow streets with high buildings, usually has difficulty maintaining accurate positioning information due to GPS signal blockage and multipath.

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