Nigerian Research Journal of Engineering and Environmental Sciences 3(1) 2018 pp. 380-387

Nigerian Research Journal of Engineering and Environmental Sciences
Journal homepage: www.rjees.com

Original Research Article

ON THE ACCURACY OF ACCELEROMETER SENSORS IN SMARTPHONE-BASED SENSING SYSTEMS

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ARTICLE INFORMATION

Article history:
Received 25 April, 2018
Revised 03 May, 2018
Accepted 03 May, 2018
Available online 30 June, 2018

Keywords:
Mobile sensing
Accelerometer sensor
Phone sensing
Pedometer
Step count

ABSTRACT

The recent advancement in mobile phone technology has led to the sophistication of smartphones. Mobile phones are now designed with several state-of-the-art sensors that can be used to acquire data from the environment. However, the validity of such data has been a subject of concern in academic fora due to discrepancies in research findings. Some results revealed that the mobile phone sensors are accurate and can be used to acquire data while others showed that the embedded sensors in mobile phones are not reliable tools for acquiring sensitive real-life data. The inconsistency in findings is the motivation behind this study, in which we juxtapose the effectiveness and accuracy of a smart phone accelerometer sensor with that of a traditional pedometer device. To achieve this, test sequence of 50, 100, 150, 200, 250 steps were performed for 3 days. For the length of 50 steps at medium intensity activity, the distance covered was calculated to be 0.037km. The smart phone accelerometer sensor also got a 50-step result and 0.030km for distance covered from activity carried out while the traditional pedometer device yielded a 44-step count and 0.017km for distance covered. The same evaluation was done at the other step counts. Results show that the step count and distance covered from the smart phone accelerometer sensor was consistent and accurate with the step count and the estimated distance for each step length, while the traditional pedometer device with pendulum sensor did not yield the estimated step count and calculated distance.

1. INTRODUCTION

The rise in the popularity, acceptance and use of smart phones as the key gadget in our daily communication is causing a corresponding increase in the interest of researchers in mobile phone sensing (Félix et al., 2015; Khan et al. 2013). Recently, research has revealed that smart phones can be designed to carry either an internal or external sensor that acquires real life, sensitive data (Ali and Khusro, 2016). The acquired data are then aggregated for use in third party mobile or web applications via an Application Programming Interface (API) offered by the phone operating system (Macias et al., 2013). Some application areas include healthcare, navigation, communication, entertainment, crowd sensing etc.

However, the reliability of the acquired data has been the subject of research over the past few years due to its increased use in health and other sensitive areas. In Zhizhong et al. (2013), the performance evaluation of four sensors that includes accelerometer, gyroscope, magnetometer, and GPS were carried out. Results revealed that the built-in accelerometer and gyroscope sensor were indeed stable with a range of 0.1 - 0.8 unit deviations between the measured value and the real value. For the compass, a 3 degrees deviation in the normal sampling rate was observed. Skandarajah et al. (2014) evaluated the effectiveness of mobile phone cameras when used as part of a mobile phone microscope with a custom mobile microscope (CellScope). Parameters such as brightness uniformity across the field of view, degree of image distortion, and nonlinear encoding of pixel intensity were used for the evaluation. The results of the study showed that mobile phone microscopes can be used to provide good and reliable images suitable for diagnostic use. Sankaran et al. (2014) evaluated the barometer sensor by using it to detect three basic user activities of idle, walking, and vehicle at extremely low-power. The data acquired from the sensor was compared in terms of power consumption and accuracy with Google's accelerometer-based Activity Recognition algorithm and Future Urban Mobility Survey's (FMS) GPS-accelerometer server-based application. Result of the comparison revealed that the barometer-based approach had a comparable accuracy to both Google and FMS and even performed better in terms of power consumption.

In McGlothlin et al. (2015), a whole-body vibration application on an iPod Touch was evaluated by obtaining 98 pairs of whole-body vibration measurements from the mobile application and a whole-body vibration device. The data was collected while operating several vehicles and mobile plant at a surface coal mine. Results show that the application could provide a 95% confidence of $+/- 0.077$ m/s^2 r.m.s. constant error for the vertical direction. Ibekwe et al. (2016) used a comparative analysis to assess the sensitivity and validity of smart phones as a screening tool for environmental noise monitoring. A sound level meter (SLM) and three smartphones running an application called Androidboy1 were used to measure noise level around Abuja, Nigeria. Statistical test of Pearson correlation, T-test and Consistency was carried out on the acquired data. Results revealed a strong correlation of $r = 0.9$ with no major difference in the p values of $p = 0.12$ & 0.58 for both day and night. The work concluded that the app is indeed a valid tool that can be used for environmental noise monitoring. Murphy and King, (2016) used broadband white noise to test the ability of 100 smartphones to measure noise at background, 50, 70 and 90 dB(A). The measurements were compared with noise levels acquired via a sound level meter. Results suggest that iOS-based smartphones showed a considerable better performance than those running on the Android platform with a revelation that there is a significant relationship between the age of a smartphone and its ability to measure noise accurately.

The accuracy of smartphone-based illuminance measurement applications and their suitability for occupational lighting measurements was carried out by Cerqueira et al. (2018). In the paper, nine different mobile phones were assembled, and 14 mobile applications were tested. Four illuminance levels of 300 lx, 500 lx, 750 lx and 1000 lx were used for the testing. Results showed that the measurements obtained from phones were varied from the reference levels. The work concluded that smartphones are not suitable for use in occupational lighting assessments.

Some results from the reviewed literature revealed that the mobile phone sensors are accurate and can be used to acquire data while others showed that the embedded sensors in mobile phones are not a reliable tool for acquiring sensitive real-life data. Due to the inconclusive result from past studies, there is a need for further studies, thus, this research work addresses this need. The aim of this work is to validate the accuracy of accelerometer sensors found in mobile phones by comparing step counts of a smartphone pedometer application with that of a pedometer device over a three-day period. Variables such as walking speed, calories burnt, and step rate were examined to determine if these variables influence pedometer accuracy.

2. MATERIALS AND METHODS

Data used for analysis was extracted from the parameters measured by the pedometer measuring devices which is A3003 Pedometer and a Pedometer Step Count & Walk Tracker by Runtastic mobile application inclusively with each having some moderate sensitivity settings for moderate and high intensity activity. A test was carried out by making an adult to walk certain distances to test drive the two devices. With the appropriate method of carrying out the tests, data was recorded in their respective order. All the taken parameters were pedometer parameters that consist of all the locomotive information of the test subject including the distance covered. Data taken into consideration includes (i) step recording (ii) speed estimate (iii) distance recorded over a fixed distance (iv) step count. The result for all these parameters were recorded by an observer. The participant involved put on the A3003 Pedometer, the Pedometer Step Count and Walk Tracker by Runtastic mobile application. At the end of each trial, step counts from each device were recorded. The mean step count, mean distance covered and the mean bias error for each device was estimated using MATLAB. Data was collated, and the necessary calculations were carried out.

2.1. A3003 Pedometer

A3003 is a pocket-sized pedometer. The A3003 has many other functions including a Step Counter, Timer, Distance meter, Speedometer, Calorie Counter, Alarm, Fat-Burning meter and Storage Memory. It uses a CR2032 battery. The device comes with an intelligent algorithm to filter out non-walking movements and alarm for step length. A continuous step mode records the number of steps users walked continuously through the day (records up to 7 days). Total step mode displays the total accumulated steps user walked after 7-day storage.

Figure 1: A3003 Pedometer

2.2. Mobile Application

The cell phone used in this research study was an iPhone running iOS operating system (iPhone operating system) and the name of the application is Pedometer Step Counter & Walk Tracker by Runtastic. The app features an automatic step detection function and can work anywhere: pockets, purse, arm or hand. It can calculate calories burned, speed, distance covered and step frequency. Users of the app can save body metrics like weight and height for a more accurate calorie count.

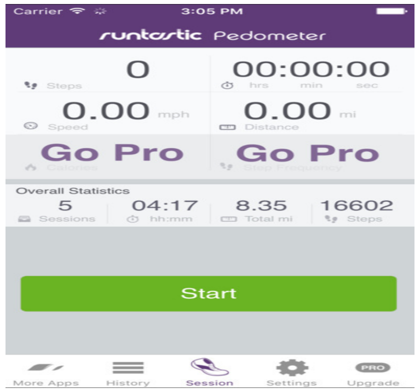

Figure 2: Runtastic Pedometer

2.3. Data Collection and Analysis

The tests subject was a male aged 23years, with a body height of 1.8 metre.

Subject's height = 1.8m = 180cm

Mass = 85kg;

$$\text{Stride length for male} = \text{Height (cm)} \times 0.415 \text{ (Vera, 2016)} \tag{1}$$

Therefore, the subject's stride length = 180 × 0.415 = 74.7 cm

Also:

$$\text{BMI (Body Mass Index)} = \frac{\text{Mass (kg)}}{(\text{Height(m)})^2} = \frac{85}{1.8^2} = 26.23 \tag{2}$$

The measurements were performed outdoors on a flat, straight road. The test person performed 50,100,150, and 200 steps with each device placed on each of two cell phone positions (i) right chest pocket (cell Phone application) and (ii) right pocket of the pant (A3003 Pedometer).

The steps were counted manually by the test person and by the test leader for each sequence of the steps. The distance was measured using a measuring wheel and time was determined using a Split Stop Watch. The walking speed was then calculated. By walking at his normal speed, the test person is expected to have walked at an average speed corresponding to the step count sequence measured in m/s. Average steps registered by each device and positions was collated. Analysis was then made by comparing all the parameters recorded using the mean bias error (MBE) that provides information on the performance of a system through comparison of the actual deviation between calculated and measured values term by term. The ideal value of the MBE is zero. The MBE is given in (So *et al.*, 2013) as:

$$\text{MBE} = \sum_{k=1}^{n} (y_k - x_k)/n \tag{3}$$

where y_k = kth calculated value; x_k = kth measured value; n = no of samples

3. RESULTS AND DISCUSSION

3.1. Actual Distances

To get the actual distances to be covered, Equation (4) was used. From the conducted study, data collected for the three days are presented in Figures 3, 4 and 5.

$$\text{Distance} = \text{Stride Length} \times \text{Step Count} \tag{4}$$

Table 1: Estimated actual distance calculated for each step count

Step counts × stride length (m)	Actual distances (km)
50 × 0.747	0.037
100 × 0.747	0.0747
150 × 0.747	0.1121
200 × 0.747	0.1494
250 × 0.747	0.187
50 × 0.747	0.037
100 × 0.747	0.0747

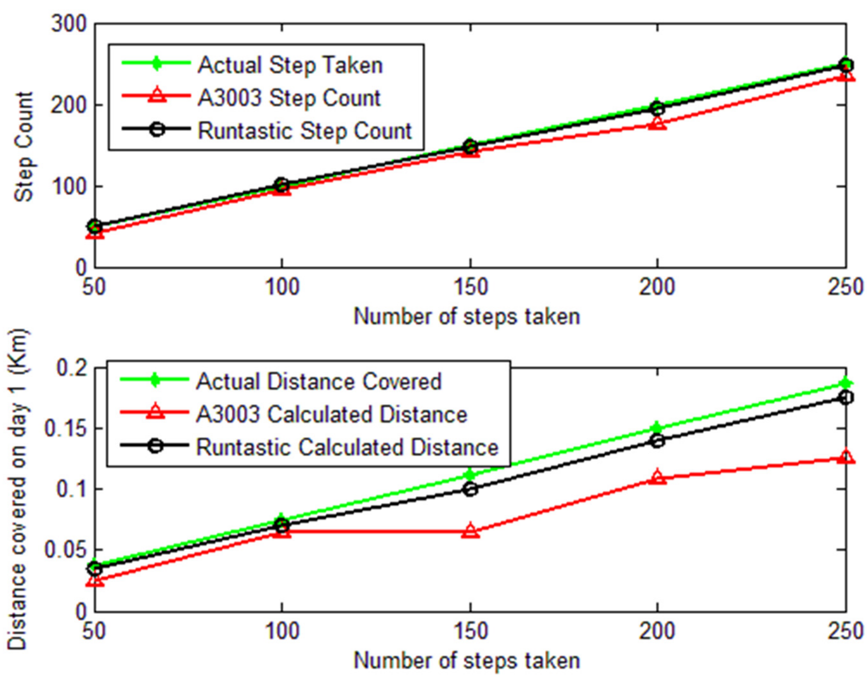

Figure 3: Step count and distance covered for day one

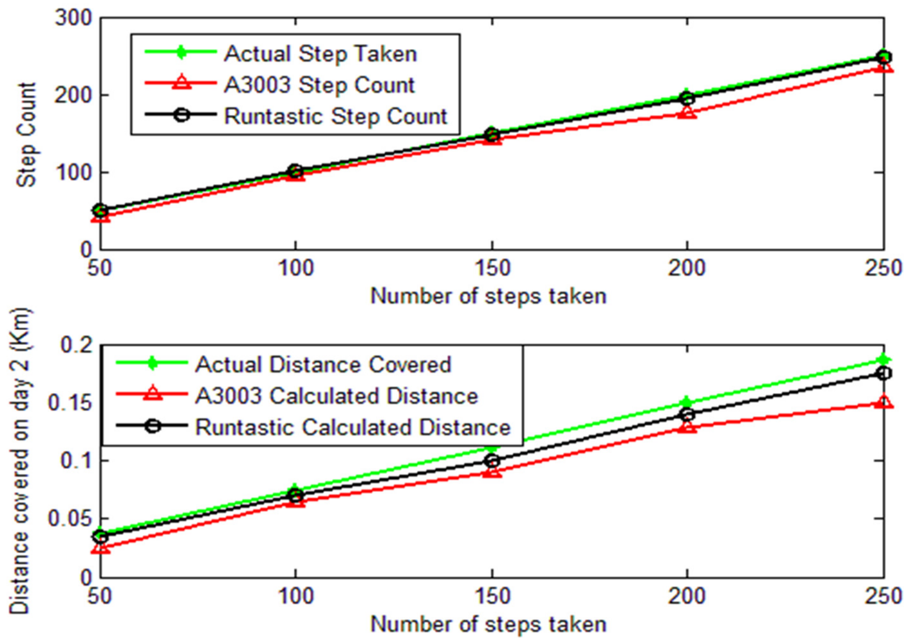

Figure 4: Step count and distance covered for day two

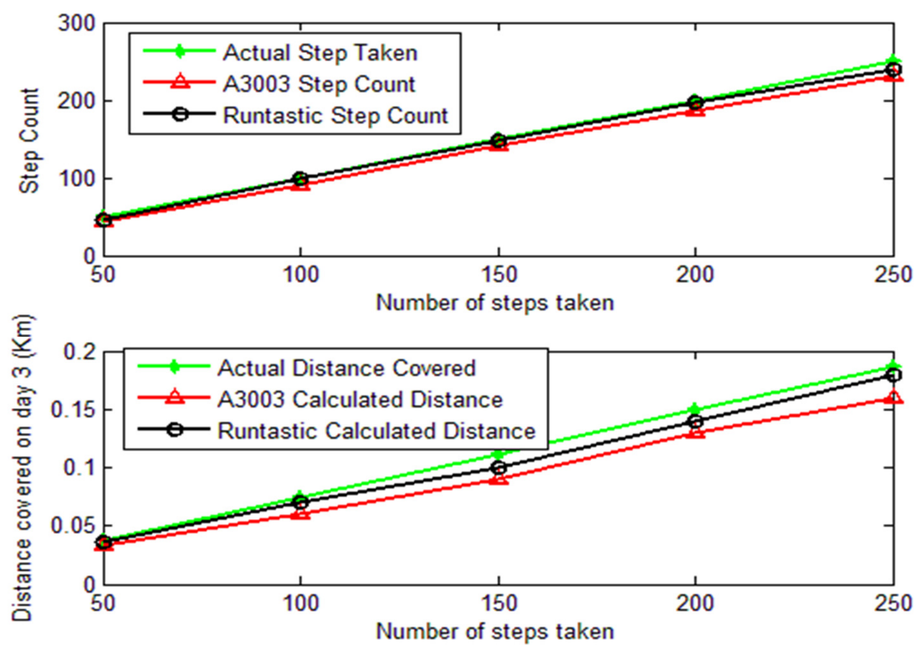

Figure 5: Step Count and Distance Covered for Day Three

Figures 3, 4 and 5 show the step count and the distance covered for the three days of evaluation. To obtain the MBE values, Equation 3 was evaluated using MATLAB and the values were obtained as output from the represented equation. To obtain the MBE value for the A3003 pedometer for distance covered, y_k is used as the calculated distance while x_k is used as the distance measured by the A3003 pedometer. The same approach was used when obtaining other MBE values. From the computations, it was observed that for the three days, between 50 and 150 steps mark, the A3003 pedometer and Runtastic (accelerometer sensor) both performed considerably well with an average mean bias error (MBE) of 0.25 and 0.2 respectively. In terms of the mean measured distance of 0.037 km to 0.112 km (50 to 150 steps), the same trend was also observed with both sensors (pedometer and accelerometer) having an average MBE of 0.35 and 0.3 respectively. However, for day 1, between 100 and 150 steps, there was a slightly higher deviation compared with the previous steps. For a step count of 200, the A3003 had an average MBE of 0.3 while the Runtastic had a value of 0.26. In terms of the estimated distance at 200 steps, the A3003 average MBE was found to be 0.36 while the Runtastic had a value of 0.29. Finally, at a step count of 250, the A3003 had an average MBE of 0.34 while the Runtastic had a value of 0.22. In terms of the estimated distance at 250 steps, the A3003 average MBE was found to be 0.38 while the Runtastic had a value of 0.2.

From the results, it can be deduced that the Runtastic application that functions using the accelerometer sensor performed better when compared to the pedometer device (A3003).

4. CONCLUSION

Due to the increasing use of smartphones as a sensing tool for capturing data from the environment and the concern about the validity of such data, this work assesses the effectiveness and accuracy of a smart phone accelerometer sensor with that of a traditional pedometer device using a statistical test method. One person performed a test sequence of 50, 100, 150, 200, 250 steps for 3 days. Measurement from the two devices were then compared and analyzed using the mean bias error. Results showed that data acquired from the smart phone accelerometer sensor is relatively accurate and can be used for scientific purposes.

5. ACKNOWLEDGEMENT

We wish to express their gratitude to Okunfolami Ibukun, a student in the Department of Computer and Electrical Engineering of Olabisi Onabanjo University for volunteering to be the test person.

6. CONFLICT OF INTEREST

There is no conflict of interest associated with this work.

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