# History-based indoor localisation system using a Smartphone

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## Abstract

Current positioning infrastructures such as Global Positioning System (GPS) are great for outdoor localisation but are limited and most of the time unavailable in indoor applications. Current smartphones provide new opportunities for user indoor localisation by leveraging low cost embedded sensors.

This paper presents an indoor positioning system using accelerometers, gyroscopes and magnetometers which are readily available in most current smartphone. The method proposed is a practical solution for smartphone-based localisation that could minimise the errors due to noise from the low cost inertial sensors and random handling condition of the smartphone by the user. The main focus in increasing the accuracy of indoor localisation system in this paper is by correcting the path taken by the user by implementing a map-based particle filter that takes into account situations where all the particles are at an invalid position and considered dead. This localisation system assumes that the map provided is complete hence positions and paths that lie outside of a valid space are considered impossible for the user to be in and invalid. Experiments have been conducted to test the performance of the proposed method. Two different Android smartphones were used and 30 samples were collected with each sample covering a distance of more than 100 metres. Results from experiments show that the proposed method was able to localise a person in an indoor environment with a mean error of less than 2 metres when the final position is compared to the real final position.

## 1 Introduction

Current localisation methods rely mostly on infrastructure such as Global Positioning System (GPS), Global Navigation Satellite System (GLONASS) or Base Transceiver Station (BTS) of a service provider. However, in an indoor environment, these infrastructures are unreliable and in worst cases unavailable due to the obstruction of a direct line-of-sight of the radio transmission by walls and roofs of buildings. The development of an accurate indoor positioning system is needed as the benefits of this application are limitless, including higher satisfaction in shopping experience, navigation for firemen in buildings filled with smoke and also reducing cross infection between patients in a hospital.

Fallah et al. [2013] in their survey outlines existing human indoor localisation solutions where GPS signals are assumed to be unavailable. Among all the methods introduced, Pedestrian Dead Reckoning (PDR) is one of the methods outlined and is feasible to be implemented using a smartphone because it uses the data obtained from an Inertial Measurement Unit (IMU) which is always available in a smartphone nowadays to predict the current position of the user. Other localisation methods which are feasible using a smartphone is triangulation and fingerprinting using either Bluetooth or Wi-Fi. Bluetooth Received Signal Strength Indicator (RSSI) based localisation techniques have been proven to be able to estimate the distance of a receiver from the transmitter by correlation the RSSI value with distance [Cho *et al.*, 2015; Jung *et al.*, 2013]. By installing multiple Bluetooth beacon and noting the position of each beacons, triangulation could be performed when three or more Bluetooth beacons are detected at once [Jianyong *et al.*, 2014]. The same implementation can also be applied to Wi-Fi hotspots as proven in research by Zhu and Feng [2013]. Fingerprinting-based localisation could also be achieved using Bluetooth and Wi-Fi signals [Kriz *et al.*, 2016; Navarro *et al.*, 2010] but it requires a database of signal strength in different locations throughout the localisation area and could be time consuming in the offline stage and infeasible if the localisation area is huge. However, both of these methods require additional infrastructure to be purchased and installed rather than just using a device which the majority of the population already own.

Smartphone based indoor localisation is an interesting topic that is still being actively researched. This is because current smartphones have built-in sensors and receivers that could be useful for localisation and have enough processing power to perform localisation methods in addition to the high rates of ownership of smartphones. Prior research proves that it is possible to perform indoor localisation utilising only the built-in smartphone IMU without needing any additional infrastructure within an acceptable accuracy [Li *et al.*, 2012]. Indoor localisation using a smartphone with the help of additional infrastructure was also proven feasible by Lui et al. [2013] by designing and building their own high-band acoustic transmitting beacons utilising network coordination protocols to localise smartphone users in different indoor environments.

This paper propose an indoor localisation system based on data collected from accelerometer, gyroscope and magnetometer inside of a user smartphone. The main focus is to increase the accuracy of the predicted position by applying a map-based particle filter that takes into account situations where all the particles collide into non-feasible region and are considered dead. The method proposed does not requires any installation of additional hardware and would only rely on the IMU embedded inside a smartphone and a complete map of the localisation area. In addition, no calibration was also done prior on the Android smartphone and no offline training was required. The conceptual idea is to correct the path generated by PDR due to the accumulation of errors especially in detecting steps and getting corresponding stride length. The proposed indoor localisation system described in this paper integrates method of indoor localisation together with correction methods. A map-based particle filter and also a history-based particle filter is integrated with the PDR in order to reduce the error produced in the path created. The proposed idea will then be evaluated with the path taken by PDR only and also PDR together with conventional particle filter through experiments in an indoor environment.

The rest of the paper is organised as follows: **Section 2** provides the PDR method used. **Section 3** describes the proposed particle filter technique used to correct the path generated by PDR. Next, **Section 4** presents the system integration implemented. In **Section 5**, the performance of the system is evaluated and compared. Finally, the conclusion and future work are outlined in **Section 6**.

## 2 Pedestrian Dead Reckoning (PDR) using a Smartphone

PDR is a method where the current position is predicted based on a known or assumed to be known previous position. Sensors such as accelerometers, gyroscopes and magnetometers are used in this recursive prediction [Fischer *et al.*, 2008]. Since the sensor embedded inside a smartphone is a low cost microelectromechanical systems (MEMS) IMU, the data obtained will be polluted with high frequency noise. PDR is based on three components: step detection, stride length of the corresponding step detected and heading estimation. Unlike normal IMU-based dead reckoning systems, which perform integration on acceleration to obtain the position from a known position [Ojeda and Borenstein, 2007] which introduces error due to the double integration, the error introduced by PDR is due to failure to detect steps or detecting false steps, inaccuracy of stride length calculation and heading estimation error. The error due to step detection leads to introducing error in stride length which will result in overestimating or underestimating the total distance travelled by the user.

### 2.1 Step Detection

Acceleration readings from a three-axis accelerometer are used to determine if a step is taken. The approach that was being used is similar to Pratama et al. [Pratama *et al.*, 2012]. Since that the orientation of the phone is unknown due to the placement of the phone on the user, the magnitude of acceleration at time $t$, $a(t)$ is calculated from the root of sum of squares of all the three acceleration components:

$$a(t) = \sqrt{a_x^2 + a_y^2 + a_z^2} - g \tag{1}$$

Where $g$ is constant to remove the influence of gravity on the accelerometer that represents the acceleration due to gravity ($9.8m/s^2$). Using the magnitude of acceleration increases the robustness of step detection as the phone could be placed in an unknown orientation by the user. Peak and valley detection of the acceleration magnitude was used to detect possible steps taken. In order to distinguish false steps with all the peaks detected, thresholding of the peaks and valley are done as applied by Pratama et al. [2013] where the maxima and minima threshold changes dynamically base of previous true value of peak and valley. The maxima and minima threshold for step $k$ is as shown in Equation 2:

$$\begin{aligned} max(k)_{threshold} &= valley(k-1) + c_{max} \\ min(k)_{threshold} &= peak(k-1) + c_{min} \end{aligned} \tag{2}$$

Where $c_{max}$ and $c_{min}$ are constants obtained from experimentation. The initial thresholds were also being

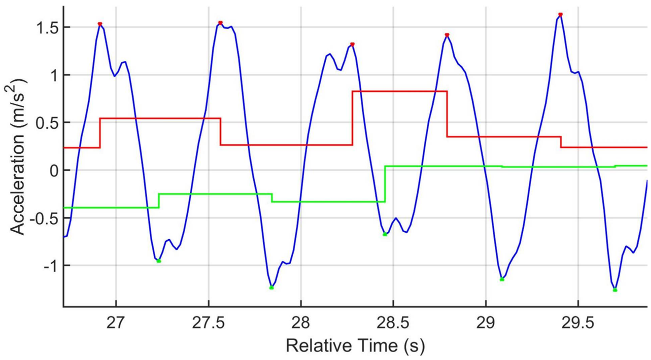


Figure 1: Part of the acceleration vs time signals used for step detection. Blue line is the acceleration data obtained from the accelerometer. The red line and the green line are the maximum and minimum dynamic threshold. Red points and green points are valid peaks and valleys detected.

defined first. Figure 1 shows a part of a detected steps by applying this step detection method. Based on the figure, the red line is the dynamic maxima threshold and the green line is the minima threshold. Green points and red points are points where true peaks and valleys are detected respectively.

### 2.2 Stride Length

In practical for a single person, the stride length of each steps differs from one another. The stride length, $d(k)_{stride}$ for step $k$ can be calculated from the magnitude of the acceleration obtained in a single step cycle by applying the an empirical formula [Bylemans *et al.*, 2009] as shown in Equation 3:

$$d(k)_{stride} = 0.1 \times \sqrt[2.7]{\overline{|a|} \times \sqrt{\frac{M}{\Delta t \times (a_{max} - a_{min})}}} \quad (3)$$

Where $t$ is the period of the step, $\overline{|a|}$ is the absolute average acceleration based on number of samples of acceleration in one step and $M$ is a constant that varies with gender. The value of $M$ could also be calibrated for an individual, but this calibration was not being performed in this study.

### 2.3 Heading Estimation

The angle with respect to the initial orientation can easily be obtained by integrating the angular rate obtained from a gyroscope. The orientation with respect to the magnetic north could also be obtained from a magnetometer. Both methods are useful in estimating the users heading but each method has its own drawbacks. The gyroscope is sensitive to minute angular changes of the human body which causes the data obtained from it to be unstable. This eventually introduces drift errors when integration of the gyroscope reading is performed. On the other hand, while orientation obtained from the magnetometer is known to maintain its accuracy over time, the magnetometer reading can fluctuate due to magnetic field disturbance which is more common in an indoor environment. Kang et al. propose fusing both orientation data by exploiting the accuracy of magnetometer and also using the gyroscope data to detect changes in the magnetometer that is due to magnetic field disturbance [Kang *et al.*, 2012]. The heading estimation in the propose indoor localisation system implements the algorithm proposed by Kang et al.

## 3 Map-based Particle filter

Previous research proved that a map-based particle filter was able to improve the position estimation accuracy of PDR [Kim and Kim, 2012]. Particles are assigned with weight and the final position estimation is based on the distribution of the particles in the valid localisation space. Initially all particles are assigned with similar weights. In this study, a single particle propagated at step $k$ is based on the heading, $\theta$ and stride length, $d$ obtained from PDR as shown in Equation 4:

**Algorithm 1** Map-based Particle Filter

```
Move all particles based on Equation 4
Get particles that are dead
if all particles are dead then
  i = 0
  n = 0
  while (number of particles)/N is dead do
    if i = 0 then
      θ = θ(k − 1)
    else if i = even number then
      θ = θ(k) + sign(θ(k) − θ(k − 1))n × c
    else if i = odd number then
      θ = θ(k) − sign(θ(k) − θ(k − 1))n × c
      n + +
    end if
    Move particles using θ based on Equation 4
    i + +
  end while
else
  for each dead particle do
    while particle is dead do
      Select a random living particle
      Find new position based on Equation 5
    end while
  end for
end if
```

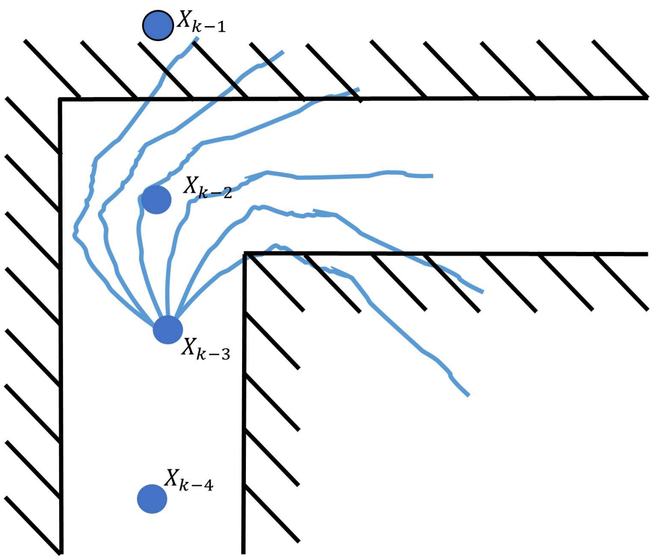


Figure 2: History fitting on previous position. Blue points are estimated positions of previous steps. In this case the path produced by PDR goes straight through the wall for a few steps before turning. In this case no psuedo-positions are required since all the pseudo-positions are going to be in a non-localisable area.

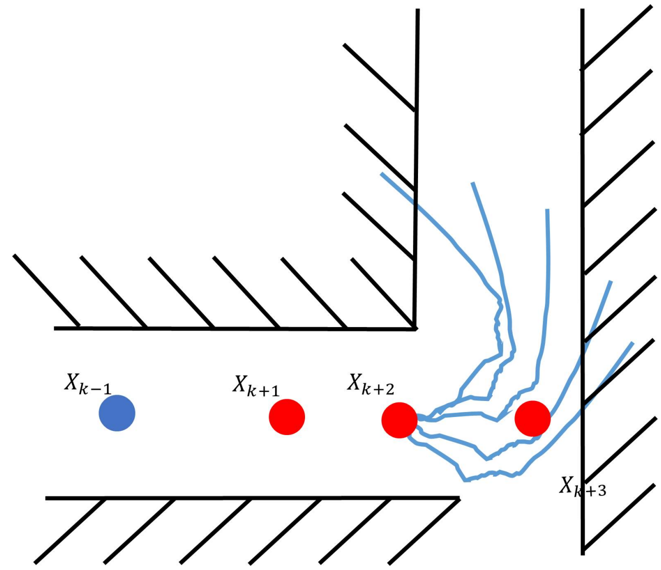


Figure 3: History fitting on pseudo-position. Blue points are estimated positions of previous steps while red points are pseudo-points created. In this case the path produced by PDR turns and goes through the wall at step $k$ where it is suppose move ahead a few steps before turning.

$$
\begin{aligned}
x(k+1) &= x(k) + (d(k) + \delta d)\cos(\theta(k) + \delta\theta) \\
y(k+1) &= y(k) + (d(k) + \delta d)\sin(\theta(k) + \delta\theta)
\end{aligned} \tag{4}
$$

Where $\delta d$ and $\delta\theta$ are the random zero mean Gaussian noise. In order to reduce computation requirements, Boolean logic is used to represent the weight of each particle with 1 being alive and 0 being dead. A particle is assigned a weight of 0 if its position is outside of a non-feasible region inside of the map or if it passes through an object. Particles with position $(x_d, y_d)$ that is dead are repositioned by selecting a random living particle of position $(x_r, y_r)$ and randomly placing it somewhere around that chosen living particle:

$$
\begin{aligned}
x_d &= x_r + \delta r \times \cos(\delta\phi) \\
y_d &= y_r + \delta r \times \sin(\delta\phi)
\end{aligned} \tag{5}
$$

Where $\delta r$ is a random number representing the distance to selected particle $(x_r, y_r)$ in the range of $[0, 1]$ metres while $\delta\phi$ is a random number representing angle in the range of $[0, 2\pi]$ in radians. The user position is the centroid position of the particles. The algorithm of the map-based particle filter is summarised in the pseudocode Algorithm 1, where $\theta(k)$ and $\theta(k-1)$ is the heading estimation at step $k$ and previous step $k-1$ respectively. c is the increment in heading constant.

### 3.1 History-based particle filter

The implementation of the map-based particle filter as described in previous section causes the path to have a different shape compared to the path generated by PDR when all of the particles are dead. Due to the correction of heading when all of the particles are dead in order to fit a path in the map, the shape of the corrected path by the map-based particle filter may deviate in comparison to the shape of the path produced by PDR. This could be undesirable since the shape of the path generated by PDR represents the real path but in a drifted manner. Guivant et al. proposed a method of using the history of path generated when a vehicle is detected to be out of the road network and used the history to deal with out-of-map vehicle localisation in a incomplete map [Guivant *et al.*, 2010]. The approach was able to deduce that the vehicle is on a road that was not included in the map. In this paper, the history-based particle filter deals with events when all of the particles are dead by saving path generated by pure PDR for 5 steps starting from the position at step $k-1$. This saved path is called the history. After detecting and saving five steps, pseudo-positions are placed in the map to represent steps $k+n$ by using heading and stride length information from step $k-1$. The history is then matched into the map by fitting the history to the position at step $k-2$ and if no solution is found, the history is then fitted to the position step $k+1$ and the fitting step repeated at $k-m$ and $k+n$

until a solution is found. Pseudo-positions are placed due to the assumption that the path could be shorter than the real path taken due to error produced during the PDR process where steps are failed to be detected. Figure 2 and Figure 3 shows the possible fitting of the history to previous positions and psuedo-positions.

## 4 System Architecture

Figure 4 shows the system integration of the proposed indoor localisation system. The overall system includes pedestrian dead reckoning, map-based particle filter and also history-based particle filter.

## 5 Performance Evaluation

The experiment was conducted using two Android phones, LG G3 and a Sony Xperia Z3 compact. Both phones are equipped with the sensors that are needed which are accelerometers, gyroscopes and also magnetometers. The experiment was conducted to test and compare the position accuracy of the path produced by PDR, PDR and map-based particle filter and also PDR and history-based particle filter. An app was designed to collect the raw sensor data from the phone at a frequency of 50Hz. The data is then being processed in MATLAB on a computer after data collection is done. The data is processed in such a way that simulates data processing in an online manner such that no future data is known beforehand. Each set of experiments was run with 3 different participants 5 times for each phone. The experiment was conducted in the Mechatronics lab and corridor of the Willis Annexe building. A path was designed and marked on the floor for participants to follow the path. The real path taken by the participant may not be the same as the marked path since participants are allowed to make a turn naturally based on their walking styles whereas the marked path has a 90 degree turn. The path covers a total distance of 109.92 metres. It took around 2 minutes to complete a single path at normal walking speed.

Based on the results, the history-based particle filter was able to further correct the path produced by the mapped-based particle filter across both devices. Figure 5 show the trajectory of the path produced by PDR, PDR and map-based particle filter and also PDR and history-based particle filter. The figure shows the worst outcome that was produced by the map-based particle filter out of all data sets collected and how the history-based particle filter were able to correct the trajectory of the path taken. The map-based particle filter wasn't

Table 1: Localisation accuracy from data collected on LG G3

| | PDR | MPF | HPF |
|---|---|---|---|
| Average error (m) | 10.75 | 6.48 | 1.89 |
| Average accuracy (%) | 90.22 | 94.11 | 98.28 |

Table 2: Localisation accuracy from data collected on Sony Xperia Z3 compact

| | PDR | MPF | HPF |
|---|---|---|---|
| Average error (m) | 10.89 | 5.72 | 0.90 |
| Average accuracy (%) | 90.10 | 94.80 | 99.18 |

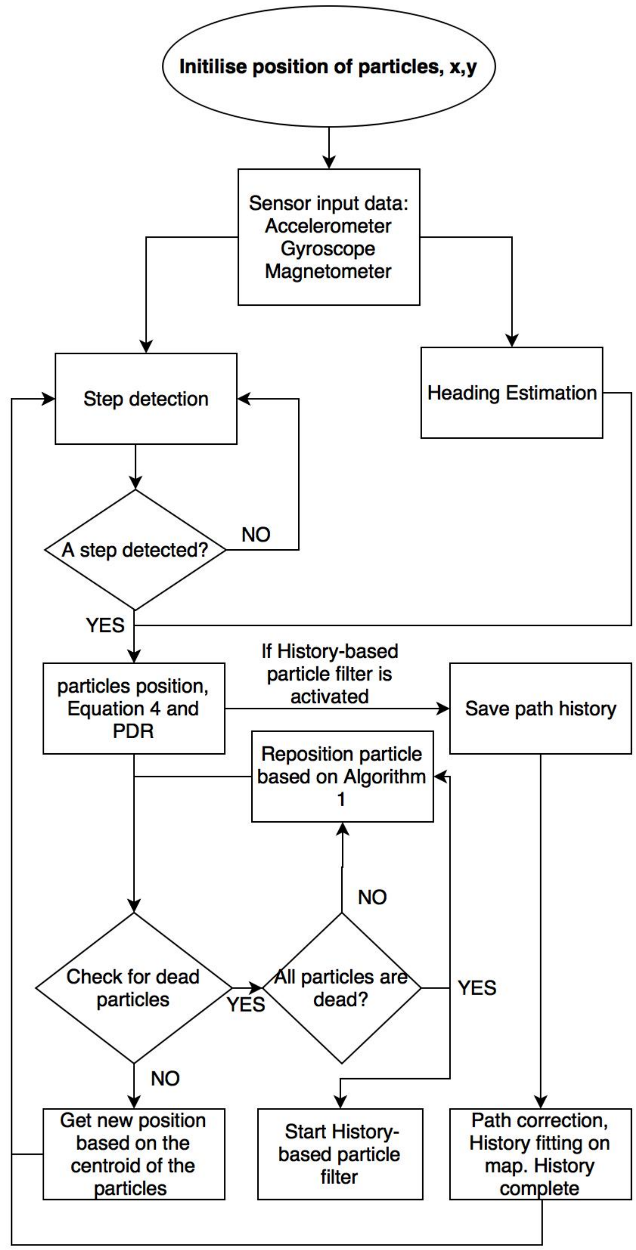


Figure 4: System architecture of the integration of the whole system consisting of Pedestrian Dead Reckoning, map-based particle filter and also history-based particle filter.

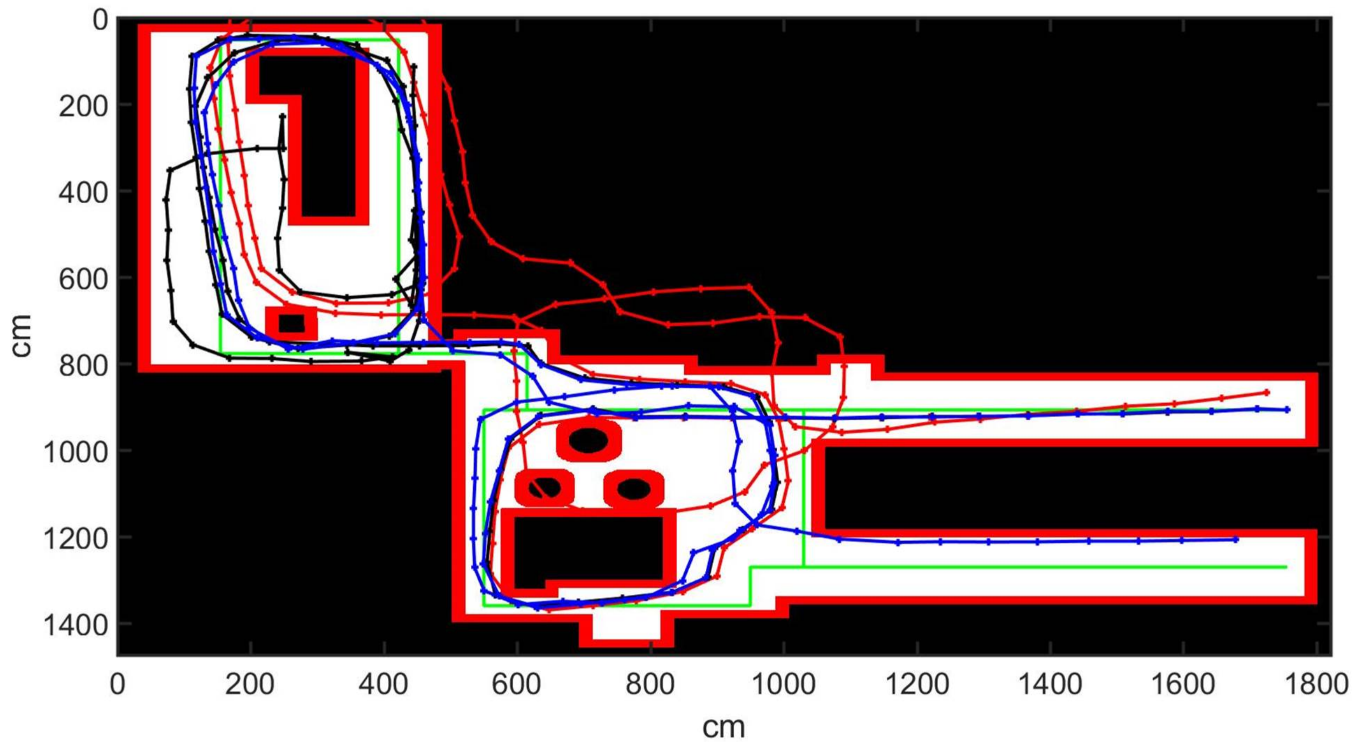


Figure 5: Path produced by three methods in a given map. White area is the localisable area and the black area is invalid region while red area is area of low probability for a position to be in. The green line represents the real path, red line represents path produced by PDR. The black line and blue line represent paths generated by the map-based particle filter and the history-based particle filter respectively. The initial position is set at point (1756, 907.4) and the real end position is at point (1756, 1271). This is the worst outcome that was produced by the map-based particle filter and shows how the history-based particle filter was able to correct it.

able to correctly produce a position in a situation where all of the particles are dead and repositioned. This situation gets worst as more steps are taken and added to the position that was already off track. Table 1 and Table 2 shows the mean accuracy in distance and also percentage of each method namely Pedestrian Dead Reckoning (PDR), PDR and map-based particle filter (MPF) and also PDR and history-based particle filter (HPF). Table 1 shows results obtained from the LG G3 while Table 2 shows results obtained from the Sony Xperia Z3 compact. In general the history-based particle filter produces the most accurate trajectory with an average accuracy of the final position compared to the real final position of 98.28% for the LG G3 and 99.18% for Sony Xperia Z3 compact. The different smartphones used did not have a significant effects on the performance of the localisation across all three methods.

## 6 Conclusion and future work

The history-based particle filter has been demonstrated to be able to increase the accuracy of localisation of a person by utilising the sensors inside of a smartphone. The method propose does not need any installation of any extra hardware other than the smartphone itself and a map of the localisation area.

Based on the results, the history-based particle filter was able to localise a person within 2 metres of accuracy. More importantly, the proposed method was able to correct the path produced by the map-based particle filter which deviates from the real path as all of particles are dead and being repositioned. In the experiment, the brand of smartphone used does not have any significant effect on the performance or the accuracy of the localisation.

Since the proposed method depends greatly on the information provided from Pedestrian Dead Reckoning (PDR), The PDR could be improved further especially the heading estimation algorithm which is the major source of error in localisation. This method could also be extended by including an infrastructural based localisation such as such including Received Signal Strength Indication (RSSI) based localisation from known positioned Bluetooth beacons or Wi-Fi hot spots in order to improve the particle filter method by checking whether the particles are in a region of high probability based on the ranges from the receivers. Since that it is important for the user to get to know their position as they walk in a real life application, the data obtained from the sensors are needed to be processed in real time. Feasibility studies need to be conducted to in order to identify the suitability of the data being processed on the smartphone itself by a low powered processor.

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