CYBER PHYSICAL SYSTEMS FOR COLLABORATIVE INDOOR LOCALIZATION AND MAPPING

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ABSTRACT

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Indoor Positioning System (IPS) is crucial for Cyber Physical System (CPS) to facilitate the interaction between humans and objects in physical and cyber world. The realization of smartphone technologies whereby many sensors (e.g. accelerometer, gyroscope and etc.) are incorporate into a single device allows many IPS techniques to be developed without the need of additional hardware. Among those techniques, Pedestrian Dead Reckoning (PDR) and Wi-Fi fingerprinting are using the technique that does not require additional hardware. While many researchers are still focusing on improving the positioning accuracy by incorporating more information from other sensors such as magnetic sensor, Bluetooth beacons, etc., this research focus on the issue of heterogeneity of smartphone models. The motivation for this issue is due to the fact that different smartphone brands and models may use different sensor chipsets and antennas from different manufacturers in their design. If the experiment of developed IPS were to test on only one smartphone, it may not provide the same level of performance or accuracy when tested on different smartphone models.

Therefore, we propose a PDR-based IPS that provides continuous position tracking. However, with the challenge of drift errors from PDR

technique, we introduce the concept of correction points which are logical points where their locations are known. Besides inferring the user's position when the user is close to the correction point(s), the proposed solution also uses the correction points to recalibrate smartphones measurements to help reduce the cumulative error in heterogeneous smartphone models. With the absence of a standard benchmark for measuring the accuracy of IPS, we also introduce a model for measuring and comparing the effectiveness of various IPS, referred to as the GreyZone model. The GreyZone model provides an abstraction to the test environment which also allows IPS with different indoor positioning techniques to be comparable. Hence, to show the effectiveness of our proposed IPS, it is experimented using the GreyZone model and compared with several existing works. From the experimental results, our proposed solution using PDR with correction points is able to perform continuous position tracking and managed to observe an improvement on positioning accuracy of more than 50% when compared to IPS that uses PDR technique alone. On top of that, we also develop a fusion of PDR and Wi-Fi fingerprinting techniques for a situation when PDR fails to provide good positioning. The proposed PDR-based IPS is utilized to perform Wi-Fi fingerprint mapping, which reduces the effort for system maintenance.

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APPROVAL SHEET

This dissertation entitled "***CYBER PHYSICAL SYSTEMS FOR COLLABORATIVE INDOOR LOCALIZATION AND MAPPING***" was prepared by JACQUELINE ANG LEE FANG and submitted as partial fulfilment of the requirements for the degree of Master of Science (Computer Science) at Universiti Tunku Abdul Rahman.

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SUBMISSION OF FINAL YEAR PROJECT /DISSERTATION/THESIS

It is hereby certified that ***Jacqueline Ang Lee Fang*** (ID No: ***16 ACM 06161***) has completed this dissertation entitled "*CYBER PHYSICAL SYSTEMS FOR COLLABORATIVE INDOOR LOCALIZATION AND MAPPING*" under the supervision of Dr. Ooi Boon Yaik (Supervisor) from the Department of Computer and Communication Technology, Faculty of Information and Communication Technology, and Mr. Lee Wai Kong (Co-Supervisor) from the Department of Computer and Communication Technology, Faculty of Information and Communication Technology.

I understand that University will upload softcopy of my dissertation in pdf format into UTAR Institutional Repository, which may be made accessible to UTAR community and public.

Yours truly,

_____

(*JACQUELINE ANG LEE FANG*)

DECLARATION

I hereby declare that the dissertation is based on my original work except for quotation and citations which have been duly acknowledged. I also declare that it has not been previously or concurrently submitted for any other degree at UTAR or other institution.

(JACQUELINE ANG LEE FANG)

Date: 17 July 2018

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LIST OF ABBREVIATIONS

CPS	Cyber Physical System
GNSS	Global Navigation Satellite System
GPS	Global Positioning System
IPS	Indoor Positioning System
VPS	Virtual Positioning Service
IMU	Inertial Measurement Unit
AR	Augmented Reality
Wi-Fi	Wireless Fidelity
PDR	Pedestrian Dead Reckoning
SHS	Step and Heading System
RSSI	Received Signal Strength Indicator
AP	Access Point
RFID	Radio Frequency Identification
UWB	Ultra-Wide Band
RF	Radio Frequency
RP	Reference Point
NN	Nearest Neighbour
k-NN	k-Nearest Neighbour
Wk-NN	Weighted k-Nearest Neighbour
PL	Path Loss
TTFF	Time-To-First-Fix
A-GPS	Assisted GPS
Gz	GreyZone
HTTP	Hypertext Transfer Protocol

CHAPTER 1

INTRODUCTION

1.1. Background Information

Accurate Indoor Positioning System (IPS) is a crucial component that is needed to extend Cyber Physical System (CPS) capabilities especially for interaction between humans and objects in physical and cyber world. This research focuses on using developing IPS on typical smartphones for human to relay their physical positions into the CPS realm while the correction points are location reference points between the cyber and physical world.

Global Navigation Satellite System (GNSS), (e.g. Global Positioning System (GPS)) has been widely used for navigation in outdoor environments. However, GNSS is not suitable to be used for indoor navigation due to signals from the satellites cannot penetrate buildings. As such, the Indoor Positioning System (IPS) has been receiving great interest from researchers in recent years (Nuaimi and Kamel, 2011; Pratama, Widyawan and Hidayat, 2012). Some of the use case for IPS are; guidance for visitors in a museum or a shopping mall, items tracking stored in a warehouse, firemen with rescue mission in a building and etc.

This work aims to develop a more accurate IPS that is able to perform continuous position tracking without using additional hardware other than a smartphone with built-in sensors such as gyroscope, magnetometer and accelerometer. Despite that there are many IPS existing works, many of them

have yet to consider the heterogeneity of smartphones which users could use to perform indoor positioning.

Many IPSs have been proposed such as active badge (Want *et al.*, 1992) and Google's Virtual Positioning Service (VPS) (*Tango Concepts*, 2017). Unfortunately, those IPSs with high accuracy often requires additional devices such as Inertial Measurement Unit (IMU) and depth sensors. For example, Google's VPS requires mobile devices with built-in depth sensors which is supported by Google's Tango Augmented Reality (AR) computing platform only (*Tango Concepts*, 2017). Similarly, combination of foot-mounted IMU with Wi-Fi fingerprinting technique (Gu *et al.*, 2017) can provide better positioning accuracy but the implementation also requires users to have shoes with IMU attached. Having additional devices on smartphones are not desirable in many occasions because it incur additional deployment cost and also not user friendly.

Hence, the advancement of smartphones with built-in sensors (e.g. gyroscope, accelerometer, and magnetometer) increases the possibilities for many IPS techniques like Pedestrian Dead Reckoning (PDR) (Radu and Marina, 2013; Akeila, Salcic and Swain, 2014; Perttula *et al.*, 2014; Kang and Han, 2015; Chen, Zhu and Soh, 2016; Pasku *et al.*, 2017) and Wi-Fi fingerprinting (Pivato, Palopoli and Petri, 2011; Boonsriwai and Apavatjrut, 2013; Bisio *et al.*, 2014; Jedari *et al.*, 2015; Schüssel and Pregizer, 2015; Wang *et al.*, 2015; He *et al.*, 2016). These techniques are becoming the mainstream despite of inferior accuracy compared to the aforementioned IPS that requires additional and dedicated hardware.

The elementary idea of the PDR technique uses the Step and Heading Systems (SHSs) to derive the current location of the user (Kang and Han, 2015;

You Li *et al.*, 2015; Yuqi Li *et al.*, 2015). As position is estimated for every step taken and detected by the user, continuous position tracking is possible with the PDR technique. Although the PDR technique requires little or no infrastructure to be installed in buildings (Harle, 2013; Akeila, Salcic and Swain, 2014), the major limitation of PDR technique is that minor errors from step length estimation and heading's direction will accumulate fast over time (Akeila, Salcic and Swain, 2014; Chen *et al.*, 2014; Kang and Han, 2015; Chen, Zhu and Chai Soh, 2016; Sheinker *et al.*, 2016). Additionally, the PDR positioning accuracy will also be affected by the variation of smartphone sensors' chipsets (e.g. smartphones with different sensitivity may estimate the number of steps, distance travelled and directions slightly differently) and different users with different heights and walking gaits as well.

The Wi-Fi fingerprinting approach that based on the Received Signal Strength Indication (RSSI) has been the focus of IPS due to the proliferation of public and private network Access Points (APs). This technique has showed promising results in many existing works (Boonsriwai and Apavatjrut, 2013; He *et al.*, 2014) and many are still focusing on improving its accuracy. One of the challenges of Wi-Fi fingerprinting is that Wi-Fi RSSI fluctuates most of the time, it is easily affected by reflection, diffraction and scattering during the propagation in indoor environments, hence, affects the positioning accuracy. Similarly, the positioning accuracy of Wi-Fi fingerprinting is also affected by the variation of smartphone Wi-Fi chipsets and antennas, and it is even more challenging to retain continuous position tracking.

Therefore, many existing works focus on improving the accuracy of PDR and Wi-Fi fingerprinting by incorporating more information from other sensors

such as magnetic sensor (Li *et al.*, 2015) and Bluetooth beacons (Shi *et al.*, 2015). There are also some existing works that fuse both Wi-Fi fingerprinting and PDR techniques (Radu and Marina, 2013; Chen *et al.*, 2014; Zhuang *et al.*, 2016). Unfortunately, these works did not consider the heterogeneity of smartphones. Different brand and model of smartphones use different sensor chipsets and antennas from different manufacturers. Kos *et al.* (2016) conducted an experiment to test on the parameters of smartphone sensors (i.e. accelerometer ad gyroscope) on eight different smartphone models. The authors concluded that the parameters that is measured from smartphone sensors showed variations in different smartphone models. A similar experiment was performed as shown in Figure 1.1 to show the variation of Wi-Fi RSSI of the same Access Point (AP) captured by different smartphone models at the same time and location.

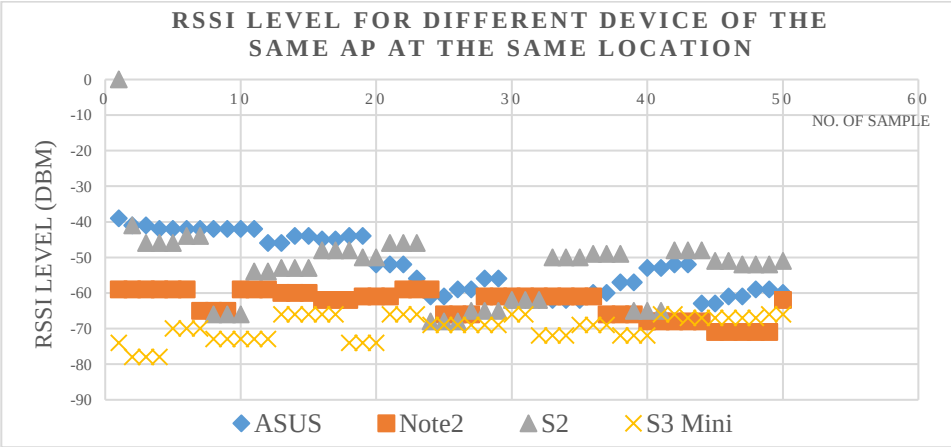

Figure 1.1. RSSI level of the same AP captured in different smartphone at the same time and location.

Figure 1.1 shows that the Wi-Fi RSSI level collected from the same AP can be very different, which eventually affects the accuracy of IPS using Wi-Fi fingerprinting technique. In addition to that, this also means that smartphones used to collect the Wi-Fi fingerprint database may not provide the same level of

accuracy when positioning is done on another smartphone that uses the same database. Collecting and updating the fingerprint database frequently will not solve the problem because it is not cost effective in the long run. Due to the fluctuations of Wi-Fi RSSI, continuous position tracking using Wi-Fi fingerprinting technique will be even more challenging (Boonsriwai and Apavatjrut, 2013; He *et al.*, 2014).

1.2. Problem Statements

Firstly, because of the consistent fluctuation of Wi-Fi RSSI through time as shown in Figure 1.1., it is **difficult to achieve continuous position tracking** using Wi-Fi fingerprinting technique (Boonsriwai and Apavatjrut, 2013; He *et al.*, 2014). Wi-Fi fingerprinting technique can only show pedestrian's position nearest to the grid-size area for fingerprint collection while the PDR technique are able to detect position closest to a step taken by the pedestrian. PDR suffers from error accumulation which will cause a large PDR drift error.

Secondly, many existing IPS works have yet to tackle on the issue of **heterogeneous smartphone models** which we opined that this is very crucial for actual deployment and usage. For instance, positioning errors are not only produced by inaccurate step length estimation from PDR technique and Wi-Fi RSSI fluctuation but also affected by varying sensor chipsets used in different smartphones and distinct walking gaits from various users.

Thirdly, despite that this work aims to use PDR to perform continuous position tracking, it is difficult to completely replace the flexibility of Wi-Fi fingerprinting technique in terms of coverage and ease-of-use. On the other hand, one of the challenges of Wi-Fi fingerprinting is to construct and maintain the

Wi-Fi fingerprint database. Therefore, a novel approach to **fuse PDR and Wi-Fi fingerprinting IPS together** is needed to create an IPS with the advantages of both techniques.

1.3. Objectives

The following are the objectives of this research:

1. To develop a PDR based IPS solution that enables continuous position tracking and improves overall positioning accuracy.
2. To design efficient approaches for PDR based IPS solution that is able to provide improvement in positioning accuracy when tested on
    i. Heterogeneous smartphone models.
    ii. Various users with different height and walking gaits.
    iii. Lesser drift error.
3. To design a novel IPS by fusing PDR and Wi-Fi fingerprinting techniques together.

1.4. Research Contributions

The major contributions of this research are as follows.

1. The proposed solution introduces correction point in which smartphones are able to identify their locations when it is near to these correction points. This approach does not only reduces PDR error drift, it also allows faster Wi-Fi fingerprinting locking.
2. This work also introduces the use of a pair of correction points to perform recalibration on positioning measurements. This can reduce PDR cumulative errors and PDR users can travel further with better positioning accuracy. The

effectiveness of this approach is compared with existing approaches and is measured using our proposed GreyZone model which will be elaborated in Chapter 4.

3. The fusion of PDR and Wi-Fi fingerprinting techniques is designed for a situation when PDR fails to provide good positioning. Concern in fingerprint database collection for mapping is resolved when the proposed PDR based IPS is used to collect and store the Wi-Fi fingerprint.

1.5. Organization of dissertation

This dissertation is organized as follows. In Chapter 2, a thorough literature review is presented to justify the research design. In Chapter 3, the discussions on methodology of proposed solution are presented and Chapter 4 discussed on the implementation and evaluation of proposed solution through a proposed modelling technique referred to as the GreyZone model. Then, the experimental conduct and results are shown and discussed in Chapter 5. Finally, Chapter 6 is the concluding chapter with some future work described.

CHAPTER 2

LITERATURE REVIEW

2.1. Basic Concepts

Indoor Positioning System (IPS) refers to the functionality of tracking a location of a person or a device in an indoor environment. Although the Global Navigation Satellite System (GNSS) strives in localization in an outdoor environment, its localization accuracy decreases in the indoor environment because of blocked signals by ceilings and buildings. As such, there are many IPS approaches that had been explored, for instance, by using Radio-Frequency Identification (RFID) (Haute *et al.*, 2015), Ultra-Wide Band (UWB) (Ruiz and Granja, 2017) and foot-mounted Inertial Measurement Unit (IMU) (Gu *et al.*, 2017). While these approaches are good in terms of positioning accuracy, the hardware required is not available on smartphones. For example, the usage of UWB based IPS requires UWB tags to be attached on smartphones (Kang and Han, 2015). Similarly, IPS using foot-mounted IMU also requires the IMU unit to be attached to the foot of pedestrians for positioning. Hence, this work focuses on IPS which uses sensors that are readily available in smartphones. This is because to have additional hardware to be attached on the smartphone are not user friendly and may incur higher deployment cost.

In general, IPS can be classified into two main categories; relative positioning and absolute positioning (Goel, Roumeliotis and Sukhatme, 1999).

1) **Relative positioning:** Relative positioning evaluates position and orientation based on information provided by various on-board sensors (e.g. accelerometers, gyroscopes, etc.). A widely known technique, the Pedestrian Dead Reckoning (PDR) technique employs simple geometric equations to compute the relative position to its starting position. Unfortunately, dead reckoning cannot be used for long distances as the localization error grows with time.

2) **Absolute positioning:** Absolute positioning obtains the absolute position based on landmarks, beacons or satellite-based signals (i.e. GPS). Several positioning principles proposed in the existing works such as trilateration, triangulation, scene analysis and proximity fall under the absolute positioning category (Nuaimi and Kamel, 2014).

    a. In trilateration algorithm, (x, y) coordinates of a position is calculated based on the distances from nearby APs. First, RSSI measurements were converted to distance between a node and AP(s). Then, by using the geometry of circles, the location of the node is computed.

    b. Triangulation is similar to trilateration, but it uses angles to get the distance. However, due to the errors from converting the RSSI measurements to the distances, the trilateration and triangulation principles could not give accurate results (Chan and Sohn, 2012). This issue is particularly serious in indoor environments as Wi-Fi signals fluctuate most of the time in the indoor environments.

c. Scene analysis is where fingerprinting is used. A fingerprint is a unique characteristic collected of an area and it is stored into a database for location identification.

d. Lastly, the proximity principle is usually used in Radio Frequency (RF) systems. The antennas are deployed at fixed locations in a building. When a mobile node is detected by those antennas, the antenna that receives the strongest signal is considered in estimating the location of the mobile node.

As mentioned in Chapter 1.2, this work is particularly interested to fuse PDR and Wi-Fi fingerprinting techniques together. Therefore, in the subsequent sections, a detail review of PDR and Wi-Fi fingerprinting techniques is presented.

2.2. IPS using PDR technique

Pedestrian Dead Reckoning (PDR) technique uses the Step and Heading Systems (SHSs) to observe pedestrian movement (Kang and Han, 2015; Lin, Li and Lachapelle, 2015; Moder *et al.*, 2015). The SHSs are acquired via the fusion of data from smartphone sensors such as accelerometer, magnetometer and gyroscope. Raw data from these smartphone sensors are used to derive the location of user in which current step length and respective heading orientation is calculated. The overall process is repeated and consists of four steps: heading orientation estimation, step detection, step length estimation and the final position estimation. The position can be expressed as

$$S_n = S_{n-1} + L_n \begin{bmatrix} sin\ \theta_n \\ cos\theta_n \end{bmatrix} \qquad (1)$$

where S_n is the coordinate of the pedestrian, L_n is the estimated step length and θ_n is the estimated heading orientation of the pedestrian at time step *n*.

2.2.1 Heading Orientation

When a pedestrian step is detected, it is important to know the direction of the step. A direct way for estimating the heading orientation is by using the magnetometer sensor but unfortunately, magnetometer sensor can be easily affected by electronic devices and metals which can be found easily in indoor environments (Li and Lin, 2013; Chen *et al.*, 2015; Kang and Han, 2015; Chen, Zhu and Soh, 2016). A common way that has been explored by many researchers are based on the fusion of accelerometer and magnetometer sensors. Accelerometer provides the gravity vector pulling and pointing of a compass towards the center of the Earth while magnetometer works as the compass. However, outputs from these sensors still have a lot of noises. Therefore, additional work is needed to eliminate those noises especially in heading orientation error. Fortunately, there is an alternative way to estimate the heading orientation which is based on the integration of gyroscope data. Although the gyroscope has very short response time, its disadvantage is the accumulated gyroscope drift due to gyroscope sensor's noise in smartphones (Harle, 2013; Chen, Zhu and Soh, 2016). In order to acquire the heading orientation, the speed values need to be integrated over time (i.e. angular velocities) which yields small errors in each computation. As the PDR current position depends on previous position, these small errors add up over time resulting in large gyro drift.

To avoid both noisy orientation and gyro drift, a fusion method of three sensors (i.e. accelerometer, magnetometer and gyroscope) is proposed by Lawitzki (Lawitzki, no date). This solution uses the gyroscope output for orientation changes in short time intervals. The combination of accelerometer and magnetometer data are used as support over long periods of time. The flow of this solution is shown in Figure 2.1.

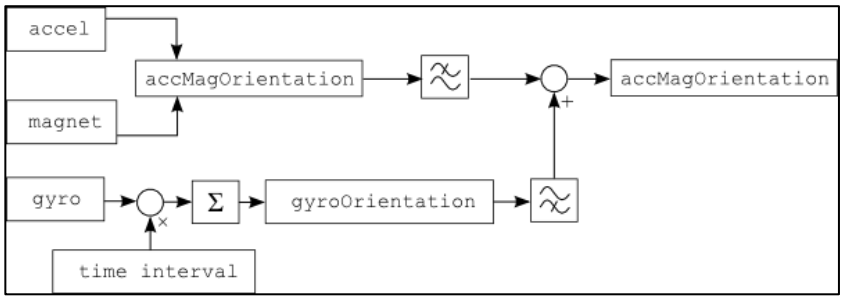

Figure 2.1. Overall flow of the sensor fusion.

Firstly, the orientation from the combination of both accelerometer and magnetometer is obtained. Meanwhile, gyroscope's orientation is obtained from a set interval of time. Then, the final heading orientation is obtained by adding both orientation outputs through a matrix multiplication and the output is transformed into compass values in degrees. This is equivalent to low-pass filtering of the accelerometer and magnetometer signals and high-pass filtering of the gyroscope signals. The expected outcome for heading orientation from the sensor fusion is as shown in Figure 2.2.

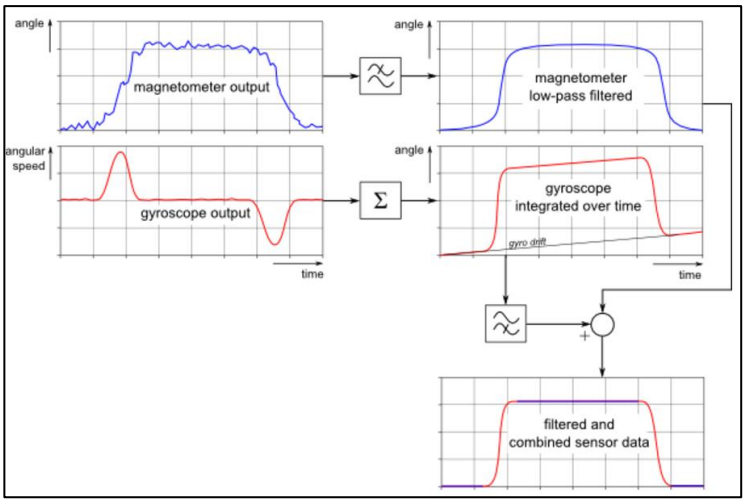

Figure 2.2. Expected output from sensor fusion.

Assuming a user walks and turns 90 degrees in one direction and after a short while, turns back to the original position. The intermediate signal of the magnetometer output in Figure 2.2 shows a smoothed signal after low-pass filtering in which the orientation angles from the combination of accelerometer and magnetometer is being averaged over time. Notice the gyroscope drift in the integrated gyroscope signal in Figure 2.2. It results from the small computation differences in the integration of gyroscope data and those small computation differences are added up upon prolong positioning. When high-pass filtering of the integrated gyroscope data is done by combining the filtered accelerometer and magnetometer values with the gyroscope orientation values, the noisy signals and gyro drift are eliminated.

2.2.2. Step Detection

Since pedestrian's travelled distance is partly represented by the number of steps taken, therefore it is necessary for the PDR technique to detect step event accurately. For step detection, accelerometer data are widely explored. However,

the accelerometer is greatly affected by the gravitational pull of the Earth. Because of that, several filters such as Kalman filter (Lin, Li and Lachapelle, 2015), low-pass filter (Kang and Han, 2015) or weighted average smoothing filter (Radu and Marina, 2013) were used by many existing works to eliminate the gravitational acceleration and for smoother raw accelerometer data or simply by subtracting the raw accelerometer data with well-known gravitational acceleration (i.e.$9.81m/s^2$). To avoid using filters which can cause complex computation, linear acceleration is explored. The linear acceleration data consist of three-axis acceleration information that is relative to the smartphone with the gravitational aspect being omitted out.

Periodic patterns can be observed in the vertical axis of the acceleration when a pedestrian's feet touches the floor during walking and it can be adapted for step detection. There are several step detection algorithms that have been implemented by many existing works, namely peak only detection, peak and valley detection (Kang and Han, 2015) and zero crossing algorithm (Harle, 2013). Peak detection algorithm is carried out by using the positive peaks from the vertical acceleration while peak and valley detection algorithm is carried out by using the positive for peaks and negative for valleys from the vertical acceleration. The vertical accelerations refer to step occurrences generated by the vertical impact when the pedestrian's foot hits the ground (Kang and Han, 2015) as shown in Figure 2.3 while zero crossing algorithm is done by counting the signals crossing zero level to determine the occurrence of a step (Radu and Marina, 2013) as shown in Figure 2.4.

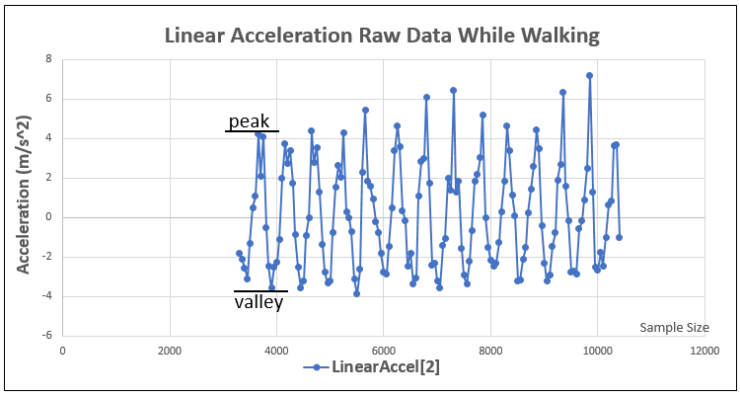

Figure 2.3. Peak and Valley algorithm for step detection.

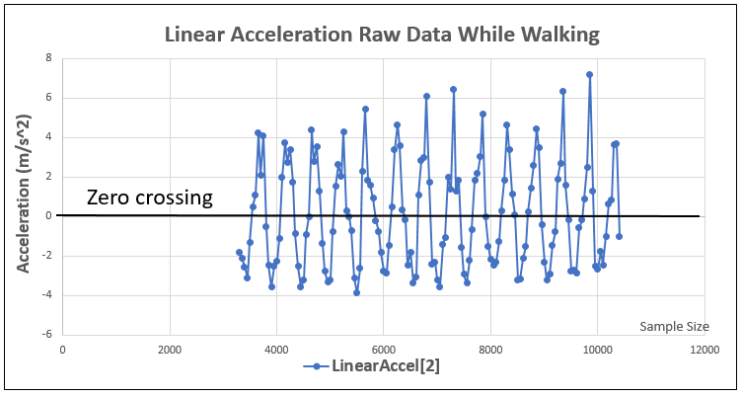

Figure 2.4. Zero Crossing algorithm for step detection.

2.2.3. Step Length Estimation

As one of the most significant parameters for the PDR technique is the step length estimation, it has large variation among not only different pedestrians' walking gaits but also in different smartphone models. Even within the same pedestrian, the step length varies significantly at every walking time. Several methods to calculate the pedestrian's step length were presented; constant step lengths and estimated step lengths based on the height input of a person. The definition of each methods are listed below:

1. **Constant step length:** This method uses constant step length for all pedestrians regardless of its walking speed and height. The step lengths are set as 78cm for male and 70cm for female.
2. **Height input:** Step length can also be estimated based on the height input of different person, which can provide more accurate results. The step length is calculated with the equation below:

$$step\ length,\ L_n = (height * K) \qquad (2)$$

Where *K* is a constant value and has different value for male and female. In this work, the constant K values are set at *K*=0.415 for male and *K*=0.413 for female, which are the same as other researchers for fair benchmarking purposes (Pratama, Widyawan and Hidayat, 2012).

While the methods mentioned above do not take deliberation of variations of pedestrian's step length during walking, an approach from Chen, Zhu and Soh (2016) constructed the relationship between vertical axis of the acceleration and step length referred to as the Weinberg approach.

3. **Weinberg approach (Weinberg, 2002):** According to the proposal from Weinberg, vertical acceleration was applied to the pedestrian's hip when he/she moves in order to determine the walking distance. Hence, the estimated walking distance is adjusted by a unit conversion, which is represented by the equation below:

$$step\ length,\ L_n = K_1 * \sqrt[4]{a_{max} - a_{min}} \qquad (3)$$

Where a_{max} and a_{min} are the maximal and minimal vertical axis of acceleration values, measured on the Z-axis for a step detected respectively. It is calculated online when pedestrian walks, it depends heavily on the walking behavior. K_1 is the unit conversion constant (i.e. feet or meters travelled), which is set as $K_1 = 0.41$ in this work for when pedestrian is walking at normal speed; this value is also used by other researchers (Pratama, Widyawan and Hidayat, 2012).

Although the Weinberg approach provides more dynamic approach to handle the variation of step length even for one pedestrian, it highly depends on sensor's data and pedestrian movements. When pedestrian's movements are not predictable, it may cause larger positioning errors. As such, the proposed solution through a pair of correction points allows auto recalibration on sensor's data and provides consistent positioning accuracy for heterogeneous smartphone models.

The PDR technique requires no additional infrastructure and enables continuous position tracking because position estimation is computed for every step taken and detected by pedestrians after leaving the starting position. Moreover, the required sensors are readily available in most smartphones, hence, no additional hardware such as IMU is needed. Unfortunately, small computation differences in the step length and heading orientation calculations in each step will be accumulated and upon prolong positioning, the PDR positioning will have significant error. This is simply because PDR technique takes reference on the previous position for the current position estimation, the disadvantage of accumulated error is a major limitation of the PDR technique.

Additionally, the PDR based IPS also requires a starting point to continue the positioning which Wi-Fi fingerprinting based IPS does not need to have (Akeila, Salcic and Swain, 2014; Chen *et al.*, 2014; Sheinker *et al.*, 2016).

2.3. IPS using Wi-Fi Fingerprinting technique

Wi-Fi fingerprinting technique is one of the most researched IPS techniques and this solution is also infrastructure-free as it uses existing Wi-Fi infrastructure. To our best knowledge, this technique can offer up to 2m of accuracy (Boonsriwai and Apavatjrut, 2013; Jedari *et al.*, 2015; Schüssel and Pregizer, 2015). It is developed based on Wi-Fi RSSI and the advantage of using existing Wi-Fi infrastructure is that the deployment cost is relatively very low compared to other IPS techniques. The conventional Wi-Fi fingerprinting technique requires two phases; offline and online. At the offline phase, the main task is to construct the fingerprint database of all access points (APs) and Reference Points (RPs) by using Wi-Fi RSSI. Then, during the online phase, current position of the user is estimated by comparing the current measured RSSI and matches them with the RSSI stored in the fingerprint database (Boonsriwai and Apavatjrut, 2013; Jedari *et al.*, 2015).

Some of the well-known fingerprinting algorithms like Nearest Neighbor (NN), Weighted k-Nearest Neighbor (Wk-NN), k-Nearest Neighbor (k-NN), path-loss (PL) and coverage area are the most common approaches in RSSI based positioning (Davidson and Piché, 2017). The NN algorithm and its generalization of Wk-NN and k-NN are also called as deterministic fingerprinting. The methods estimate the location of a node by comparing the

stored fingerprints in the database with the RSSI values measured by smartphones at every point of time. Then, estimated location is computed in the RSSI measurement of all detected APs based on the minimization of Euclidean distance. In this work, the k-NN fingerprinting algorithm is used for Wi-Fi fingerprinting based position estimation. The position estimations are based on *k* calibration points in which the most similar RSSI value sets are selected. In addition, the *k* value should be small and the optimal *k* value is about 3 to 4 for typical cases (Davidson and Piché, 2017).

Unfortunately, positioning accuracy of this technique is affected by the Wi-Fi RSSI volatility and also the grid granularity used to create the fingerprint database. For instance, if collected real-time RSSI data deviate a lot from the fingerprint map at every different point of time even when using the same device, the positioning accuracy will fluctuate even more when positioning is done on heterogeneous smartphone models. To improve the positioning accuracy by repeating the collection of fingerprint process more frequently is tedious and would incur more cost to maintain the fingerprint database. Furthermore, by adding extra APs to aid positioning will not only add interferences to the existing signals, it also cannot assure for a better positioning accuracy (Wang *et al.*, 2015) and even so it is going to be more challenging to achieve continuous position tracking by using this technique.

2.4. Issue of heterogeneous smartphone in IPS

Table 2.1 shows the categorization of various IPS approaches with the focus of improving positioning accuracy including the number and model of

devices used for experiments were also recorded. From Table 2.1, most of the reviewed existing works use only one smartphone and minority use up to two smartphones during the experiments. Kos *et al.* (2016) conducted experiments to show the significant of heterogeneity of smartphones' sensors like accelerometer and gyroscope from eight popular smartphone models. The authors concluded that the measurements captured by the smartphone sensors showed variations between heterogeneous smartphone models.

Similarly in another work, Jun *et al.* (2017) showed concern on the issue of heterogeneity of smartphone models. The authors improved the conventional Wi-Fi fingerprinting technique by directly assigning a unique sequence to each region for every smartphone respectively to reduce heavy training in the fingerprint database and device's heterogeneity. This approach effectively reduces the effect of inconsistency in Wi-Fi signal measurement for various smartphone models. Although the authors focused and tackled on the heterogeneity of smartphone models, continuous position tracking is still not possible to be achieved using Wi-Fi fingerprinting technique alone. In conjunction to our proposed correction point concept, the proposed unique sequence by Jun *et al.* (2017) is a good approach to be used as logical points in this work.

The concept of having reference points (i.e. beacons, correction points) for IPS is also not new. Similar concept has been explored by Shi *et al.* (2015) and Chen *et al.* (2015) whom proposed the usage of iBeacon to improve on positioning accuracy by pin-pointing and correcting the location when iBeacon is detected. However, the benefits and concept of its reference points are not

fully explored. On the contrary, our proposed correction points, in addition to pin-pointing the correct position, they can be used to recalibrate smartphones' sensor measurements from time to time.

Table 2.1. Categorization of the state-of-the-art work

		Experiments Performed Using		
IPS approach used	**Proposed Solution**	**Single Device**	**Multiple Device**	**Simulation**
Dead Reckoning	(Kang and Han, 2015) Computing the displacement of pedestrian through step event detection.		√ (Samsung Galaxy Note and Samsung Galaxy Note 2)	
	(Moder *et al.*, 2015) Motion recognition is presented based on classic machine learning techniques through PDR approach.	Not Stated		
	(Lin, Li and Lachapelle, 2015) Integrating dead reckoning with INS and developing Kalman filter to process for better positioning accuracy.	√ (An android smartphone)		
Wi-Fi fingerprinting	(Boonsriwai and Apavatjrut, 2013) Eliminating some Aps with lower RSSI signals	√ (Sony Xperia Sola)		
	(He *et al.*, 2014) Applying Gaussian process regression to train collected Wi-Fi RSSI dataset. Particle filter used for estimation of smartphone's location.	√ (iOS)		
	(Jun *et al.*, 2017) Applied dynamic region partitioning and directly assign unique sequence to each region as a fingerprint to handle heterogeneity of smartphones.		√	
Wi-Fi + Magnetic	(Yuqi Li *et al.*, 2015) Uses magnetometer-aided Wi-Fi considering the orientation impact on the measurements.	√ (Google Nexus Tablet)		
Wi-Fi + Dead Reckoning + Magnetic matching	(You Li *et al.*, 2015) Initial position is estimated by Wi-Fi while initial heading is estimated by integrating magnetometer and gyroscope.		√ (Samsung Galaxy S4 and Xiaomi 4)	
Wi-Fi + Dead Reckoning	(Radu and Marina, 2013) Adding activity recognition to dead reckoning solution.	√ (HTC Nexus One Smartphone)		

Wi-Fi + iBeacon	(Shi *et al.*, 2015) iBeacon divides the area, one with the combined ibeacon and another with only Wi-Fi fingerprint data and it localization is done part by part.			√
Dead Reckoning + iBeacon	(Chen *et al.*, 2015) Applying iBeacon technology to dead reckoning approach	√ (Google Nexus 4 smartphone)		

2.5. No standard benchmark for measuring accuracy of IPS

In addition to the challenges of creating more accurate IPS, Adler *et al.* (2015) conducted intensive survey on various IPS and concluded that high percentage of publications fails to present a detailed experiment process of gathering the ground truth data. Hence, manual measurements of the ground truth using distance meters were assumed. Furthermore, it is hard to validate, reproduce and improve on the results independently without full disclosure of the experiments.

Besides, several existing works (Akeila, Salcic and Swain, 2014; Ruiz and Granja, 2017) also highlighted the difficulty of measuring IPS performance. In order to show the reliability of their proposed work, they experimented several IPS performance in various locations (e.g. industrial warehouse containing diverse obstacles). It is difficult to repeat and verify the success of those proposed methods at different locations. In addition to that, Ruiz and Granja (2017) also stated that a common framework with the same test conditions for measuring the accuracy of any IPS would be useful for comparison. Therefore, this work also presents a novel method for measuring and comparing the effectiveness of various IPS through a modelling technique, which is referred to as the GreyZone model and will be discussed in Chapter 4.

2.6. Summary of Literature Review

This chapter has covered the basic concepts of IPS that showed many approaches had been explored for IPS such as RFID, UWB and IMU. While the aforementioned are good in terms of positioning accuracy, they required specific hardware that are not available in smartphones. Hence, this work focuses on PDR and Wi-Fi fingerprinting techniques as they utilize smartphone sensors and require no additional infrastructure to be attached on the smartphone. IPS techniques can be categorized into two positioning categories; relative positioning which estimates position based on information provided by on-board sensors and computes every position relative to its starting position. An example of such behavior is the PDR based IPS. Another positioning category known as the absolute positioning obtains position based on a certain landmarks or beacons like the Wi-Fi fingerprinting based IPS that stored unique fingerprint of each area for position estimation.

Wi-Fi fingerprinting technique has proved their practicality in many existing works (Boonsriwai and Apavatjrut, 2013; Jedari *et al.*, 2015; Schüssel and Pregizer, 2015; He *et al.*, 2016). However, the technique requires intensive collection and constant maintenance of the fingerprint database which is very time consuming and not cost effective in the long run. Because Wi-Fi RSSI fluctuates most of the time, it is a problem to create a universal Wi-Fi fingerprint database and not to mention the challenges of continuous position tracking in Wi-Fi fingerprinting technique. On the other hand, the PDR technique is able to provide continuous position tracking but its error accumulation upon prolong positioning is a huge limitation. In addition to that, the accuracy of PDR is also

affected by heterogeneous smartphone models, user's height and walking gaits. Several existing works also show concern on IPS accuracy on heterogeneous smartphone models whereby an experiment conducted by Kos *et al.* had showed significant difference in the measurements of smartphone sensors (i.e. accelerometer and gyroscope) captured in different smartphone models. Besides, Table 2.1 presented in this work shows that most of the existing works that had been reviewed use only one smartphone in their experiments and the solutions may not provide the same level of accuracy when tested on heterogeneous smartphone models.

Therefore, this work proposes a novel approach to fuse PDR and Wi-Fi fingerprinting IPS and create an IPS with the advantages of both techniques. The involvement of correction points will provide improvement in positioning accuracy and drift errors and at the same time, reduce the challenges in maintaining Wi-Fi fingerprint database. In addition, the issue where there is no standard benchmark for measuring the accuracy of IPS makes it hard to validate, reproduce and improve on existing works. Hence, this work also presents the GreyZone model to facilitate the comparison of positioning accuracy on different IPS. It also includes the guidelines for others to replicate and conduct experiments at different environments.

CHAPTER 3

RESEARCH METHODOLOGY

3.1. Introduction

The aim of this work is to develop an IPS which is able to perform continuous position tracking and work on heterogeneous smartphone models via the fusion on PDR and Wi-Fi fingerprinting techniques.

In our design, the PDR technique is used for its ability of continuous position tracking and Wi-Fi fingerprinting technique is applied for the correction point's detection. In the event that when the PDR technique is unable to infer a pedestrian location, the solution will switch to conventional Wi-Fi fingerprinting technique until a correction point is detected to resume PDR positioning technique. The concept of correction points are elaborated in the next section.

The correction points are also introduced to solve the heterogeneity of PDR in IPS. Therefore, the proposed IPS will not be limited to only one pedestrian and one smartphone but many pedestrians of different gender and heterogeneous smartphone models.

In addition, while PDR is used for positioning, collection of Wi-Fi RSSI values will be recorded and stored in the fingerprint database. By doing this, it eases the challenges of manual collection and maintenance of Wi-Fi fingerprint database. The overall system flow is shown in Figure 3.1.

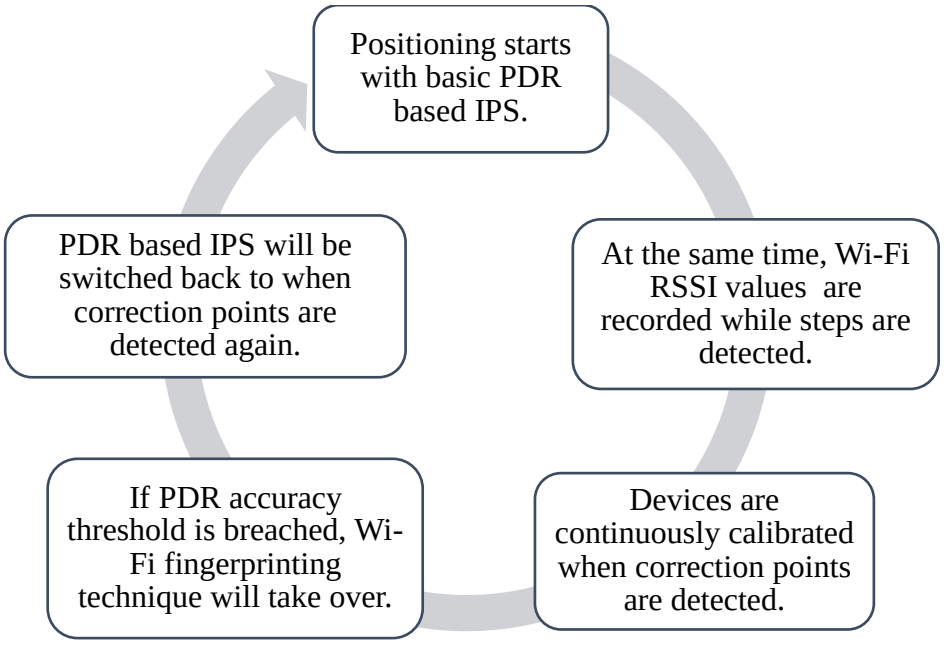

Figure 3.1. Overall system flow of proposed solution.

3.2. The PDR technique

The process of PDR-based IPS starts by acquiring smartphone sensor's data to compute for step detection, step length estimation and heading orientation estimation as shown in Figure 3.2.

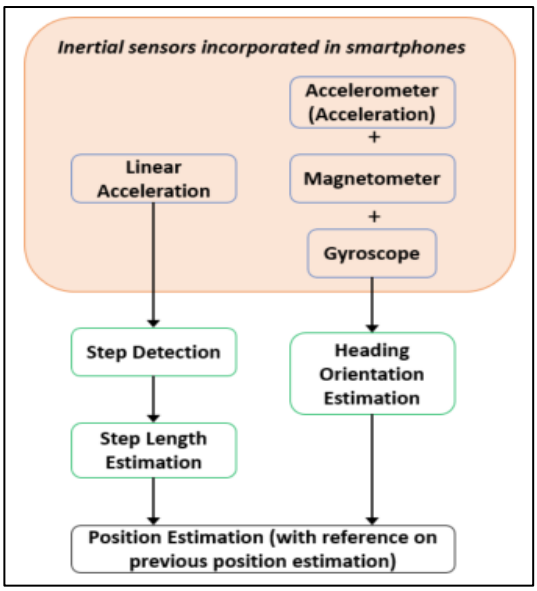

Figure 3.2. Process of PDR approach.

As aforementioned in Chapter 2.2.2 on the algorithms for step detection, this work uses the peak and valley detection algorithm with additional threshold value to detect true pedestrian steps. Because there is no filters needed for smoothing the raw data, instead, an additional threshold is used to eliminate positive and negative extremes that were not considered as true steps.

Step length in this work is estimated through the calibration by a pair of correction points. Further details on the concept of correction points is discussed in the next section.

For heading orientation estimation, fusion of three sensors (i.e. accelerometer, gyroscope and magnetometer) proposed by Lawitzki (no date) is used to avoid both noisy orientation and gyro drift. A simple test case for the sensor fusion is conducted whereby the smartphone was held on hand while walking and the result is shown in Figure 3.3.

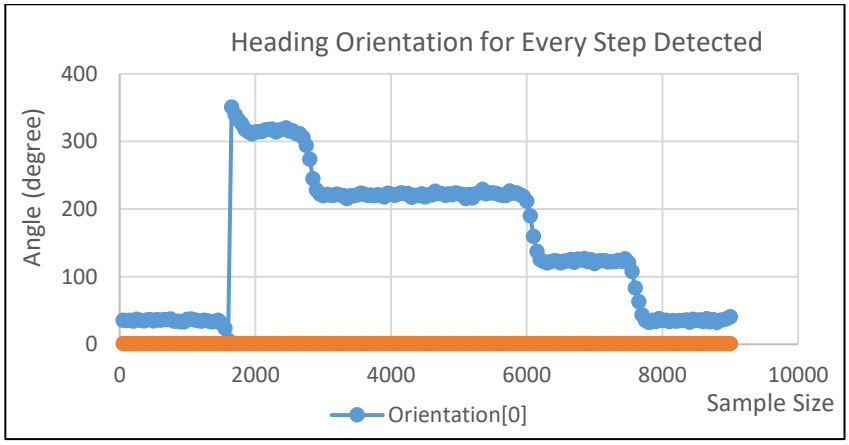

Figure 3.3. Experimental results from sensors fusion.

In Figure 3.3, pedestrian walks from a starting point, makes four almost 90 degrees turn and returns to the original position. The end result of the heading

orientation circled back to its origin with stable heading estimation without extremes which matches the expected outcome in Chapter 2, Figure 2.2. As such, the sensor fusion method for heading orientation estimation proves to have reduced the noisy sensors data from the accelerometer, magnetometer and gyroscope drift to a minimum.

The current position is then estimated based on the nature of its relative positioning by taking into consideration of the previous positions which can be expressed by formula (1) in Chapter 2.2.

3.3. The concept of "correction points"

This work introduces correction points which are logical points with known location. These points provide absolute position information without ambiguity for smartphones when they are within its respective sub-meter proximity. The sub-meter proximity is needed to share its location information accurately to the smartphones. In addition to that, the advantages of these correction points are as follows; and the fusion between PDR and Wi-Fi fingerprinting techniques is discussed in the following section. However, the optimal number of correction points and the optimal placement of correction points in a building are yet within the scope of this research due to time constraints.

3.3.1. Improvement on the positioning performance; Time-To-First-Fix (TTFF) because of sub-meter proximity detection.

Correction points are implemented by a simplified Wi-Fi fingerprinting technique in which the region for detection is reduced to sub-meter. By reducing the region for detection, the correction points work similarly as the Assisted GPS (A-GPS) that improves the start-up performance (i.e. time-to-first-fix) upon detection. Additionally, it also enhances quality and precision because signals fracture at further distance from a target. As such, accuracy decreases due to signal waiting.

3.3.2. Single mode of correction point allows adjustment and improving PDR map.

Accumulated errors from PDR technique resulting in large drift error reduces positioning accuracy over time. Other than being a point to pinpoint the location of a user, a single correction point can be used as a reference for the PDR to adjust the position accuracy of all the future steps which improves the accuracy and drift of overall continuous position tracking.

3.3.3. Recalibration on smartphone measurements through a pair of correction points for heterogeneous smartphone models and users' characteristics.

In addition, a pair of correction points can be used to calibrate the positioning measurements as the speed and duration taken to travel from one point to another point can be accurately captured. Such information can then be served as the ground truth to recalibrate the readings captured from the smartphones. Using the PDR technique as an example, the direction and the number of steps taken to travel between two correction points can be used to recalibrate the readings captured from the smartphones. Hence, drift errors of PDR can be reduced, every time user walk passed a pair of correction points. The use of correction points solves not only the issue of heterogeneous smartphone models but also different pedestrians' walking gaits as well.

The PDR correction in this work is done by calibrating the most influential parameters in the PDR (i.e. step length estimation). A pair of correction points is set up similar to that in Figure 3.4 with a set distance, d_c. Recalibration will only be done at the second correction point and a smartphone is required to detect both correction points. The correction in PDR progresses as follow:

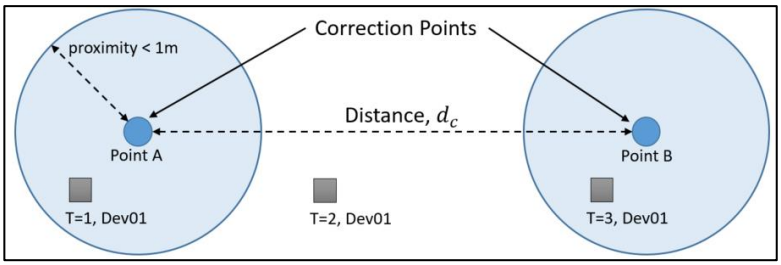

Figure 3.4. Set up for of correction points in a pair.

1) When Dev01 enters the proximity of correction point A, it records the accumulated steps taken by pedestrian.
2) Dev01 continues positioning and when it enters the proximity of correction point B, the accumulated steps taken by pedestrian will be recorded again.
3) With the known distance, d_c between the correction points and the total step taken (from the correction point A to the correction point B), recalibration towards the step length estimation can be expressed as,

$$step\ length,\ L_n = \frac{d_c}{N} \qquad (4)$$

Where d_c is the distance between the two correction points and N is the number of steps recorded from the correction point A to the correction point B.

An example of use case for PDR correction whereby distance, d_c between the two correction points are set at 10 meters. With the set distance at 10 meters and the total step taken from the correction point A to the correction point B (e.g. 15 steps), recalibration towards the step length estimation is recalibrated to

$$step\ length,\ L_n = \frac{100\ cm}{15} = 66.67cm$$

It is important to note that for the proposed correction points to calibrate PDR, pedestrian must walk in a straight line between the two correction points. Fortunately, walking in straight line can be easily detected by the heading estimation.

3.4. Fusion of PDR with Wi-Fi fingerprinting

The proposed solution allows switching from PDR based IPS to Wi-Fi fingerprinting based IPS when PDR fail to provide good positioning. For example, some indoor environments do not have many straight paths or corridors, PDR may not work well as the user's step length and heading estimations may vary for different turnings. Moreover, user may not always walk in a straight line; if there are too many turnings made, PDR will produce larger drift errors. Hence, by fusing PDR with Wi-Fi fingerprinting, we can have another IPS to function under such circumstances to allow good user experience.

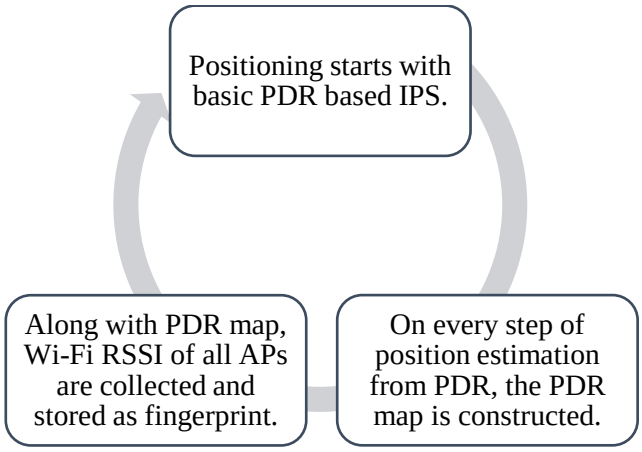

Figure 3.5. Overview process of Wi-Fi fingerprinting mapping through PDR map.

The conventional Wi-Fi fingerprinting technique requires the creation of a fingerprint database during the offline phase. From our literature review, manual collection and maintenance of fingerprint database to cater for heterogeneous smartphone models are not productive. On the contrary, the proposed solution using PDR based IPS discussed above can be used to perform Wi-Fi fingerprint collection and maintenance as shown in Figure 3.5. When the user uses PDR to perform positioning, the Wi-Fi RSSI values will also be recorded and stored in the fingerprint database. This reduces the effort of maintaining the fingerprint database manually from time to time. Then, during the online phase, the k-NN algorithm is adapted for Wi-Fi fingerprinting location estimation. This method locates by taking the k-NN nodes of the target by computing Euclidean distance between the target and all the fingerprint that is stored in the fingerprint database. According to our literature review, for typical cases, the optimal *k* value is about 3 to 4 (Davidson and Piché, 2017). Hence, all the possible position estimation within this range of *k* values are taken as the target position estimation. The implementation is further discussed in Chapter 4.

3.5. Summary

This chapter has covered the research methodology on proposed solution which aims to develop a PDR based IPS that is able to perform continuous position tracking and improves on positioning accuracy when tested on heterogeneous smartphone models via correction points. The correction points provide improvement on the positioning performance and allow adjustment on the PDR map. In addition, recalibration on smartphone measurements are also

possible through the detection of a pair of correction points. Fusion between PDR and Wi-Fi fingerprinting techniques are developed so that when PDR is unable to provide user's location due to error drift, Wi-Fi fingerprinting technique is switched to, to provide good user experience.

CHAPTER 4

IMPLEMENTATION AND EVALUATION OF SYSTEM

4.1 Introduction

As discussed in the previous chapters, the proposed solution uses smartphones for sensors data acquiring and processing. Hence, an Android mobile application is developed. Firstly, all the required sensors' data are acquired by using the Android sensor framework. Then, the data are processed according to the PDR technique requirements such as obtaining the step detection and heading orientation. For every step detected, the heading orientation, the estimated step length and the Wi-Fi RSSI of all detected APs will be recorded. With all these information that are gathered for every step, the coordinates of the user are computed by using the trigonometry function.

The fusion between PDR and Wi-Fi fingerprinting techniques is done by determining when PDR is unable to confidently provide the position of the user. In this work, a simple detection method is developed to detect when the user is walking in a zig-zag pattern which is further elaborated in the later part of this chapter (Refer to Chapter 4.6). When this event is encountered, the Wi-Fi fingerprinting IPS will take over the IPS. The Wi-Fi fingerprinting will remain as the main IPS technique until the smartphone detects a correction point, it will switch it back to use the PDR based IPS by taking the correction point's location as the starting point for the PDR technique.

Last but not least, the evaluation of the proposed solution will be conducted by using the proposed GreyZone model. An overview of the implementation of proposed IPS is as shown in Figure 4.1.

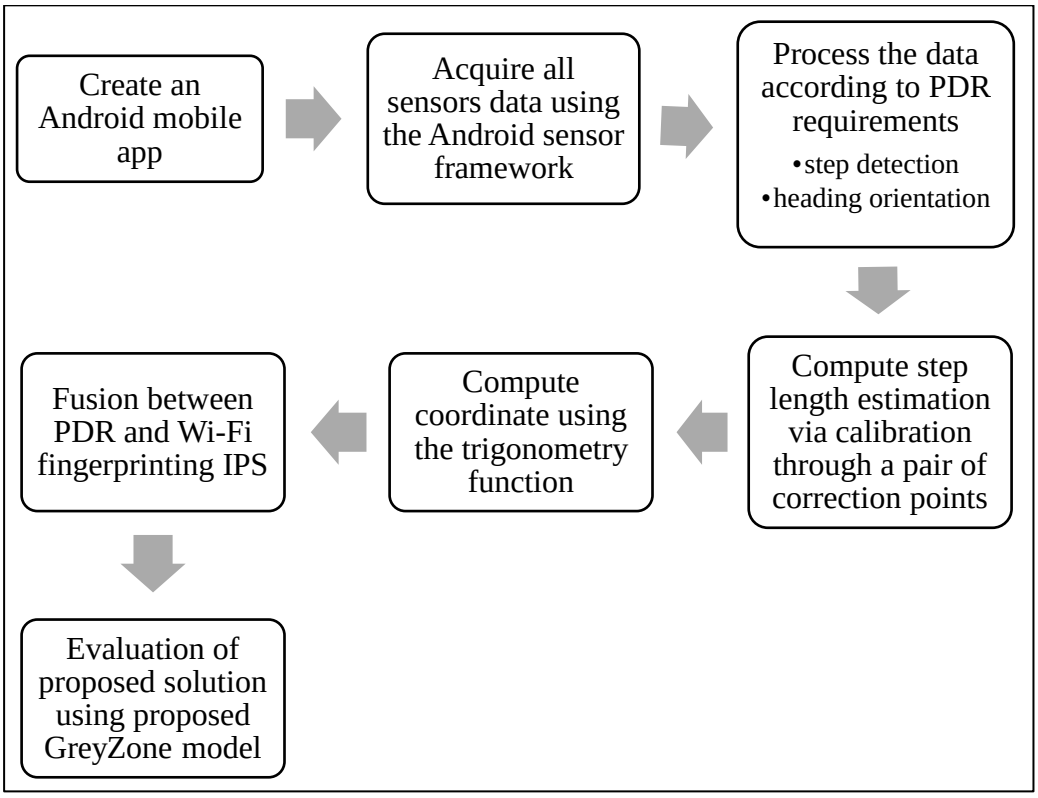

Figure 4.1 Overview of the implementation of the proposed IPS.

4.2 Android Sensor Framework

The Android sensor framework provides access to many types of sensors. In this work, we utilizes the following:-

1. Motion sensors: These sensors compute the acceleration forces and rotational forces along 3-axis (x, y and z). E.g. accelerometers and gyroscopes.

2. Position sensors: These sensors compute the physical position of a device. E.g. magnetometers.

The sensors mentioned above are hardware-based sensors whereby physical components are built in the smartphone itself. Meanwhile, the software-based sensors are not physical components. The software-based sensors, for example, linear acceleration and gravity sensors acquire their respective data from one or more of the hardware-based sensors.

Sensors used in this work are sensors that are supported by the Android platform. They are listed with their respective description in Table 4.1.

Table 4.1. Sensor types used that are supported by Android platform.

Sensor	**Description**
TYPE_ACCELEROMETER	Measures acceleration in m/s^2 that is applied on all 3-axis of a device including gravity.
TYPE_GYROSCOPE	Measures rate of rotation in rad/s of a device around each of the 3-axis.
TYPE_MAGNETIC_FIELD	Measures the geomagnetic field strength in micro-Tesla (μT) that is applied on all 3-axis of a device.
TYPE_LINEAR_ACCELERATION	Measures the acceleration in m/s^2 that is applied on all 3-axis of a device excluding the force of gravity.

4.3 Processing of raw data according to PDR requirements

After acquiring the raw sensors data, the data will be processed for step detection and heading orientation.

4.3.1 Step detection

The step detection for PDR in this work requires the linear acceleration sensor (i.e $linear\ acceleration = acceleration - acceleration\ due\ to\ gravity$). As aforementioned, the vertical axis of this sensor will contain periodic pattern on the walking motion. So, the peak and valley algorithm with an additional threshold is applied for step detection. In other words, for every peak and valley detected within the threshold value, a step taken by user will be counted. The threshold values are added to avoid positive and negative extremes values. Threshold value for peak detection is set between 1.5 and 10.0 while the threshold value for valley detection is set between -1.1 and -5.5.

4.3.2 Heading orientation

The heading orientation in this work uses three sensors; accelerometer, magnetometer and gyroscope. The overall flow of the sensor fusion is as shown in Figure 4.2.

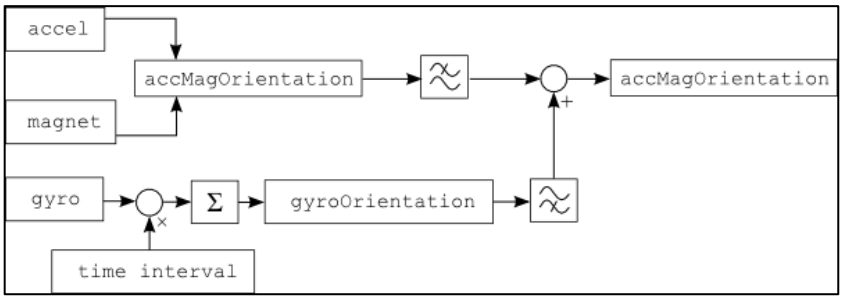

Figure 4.2 Overflow of the sensor fusion.

The sensors fusion works by firstly obtaining the rotation matrix from the accelerometer and magnetometer (accMagOrienation). Then, the gyroscope orientation (gyroOrientation) is added on the accMagOrientation at a set time interval through matrix multiplication upon the 3-axis. The final output is then converted into compass values in degrees (0 degree to 360 degree).

4.3.3 Recording and storing of Wi-Fi RSSI

At the same time, the smartphone will also consistently scanning through the Wi-Fi RSSI of all APs. When a true step is detected, the current Wi-Fi RSSI of all the APs detected will be assigned to that particular step to be stored in the fingerprint database. The data are sent to the Cloud via Hypertext Transfer Protocol (HTTP) that is designed to allow communications between clients and servers. The method use to submit the data to the server is by using the POST method.

4.4 Compute step length estimation via calibration through a pair of correction points

The step length is estimated using the proposed calibration through a pair of correction points as discussed in Chapter 3.3.3. The correction points' detection is via Wi-Fi RSSI. As aforementioned, smartphone can detect correction points when it is within its respective sub-proximity. To make the detection within a sub-meter proximity, the Wi-Fi RSSI value must be detected at greater than -55 dBm. An experiment is done on the TTFF of Wi-Fi RSSI values which will be discussed in Chapter 5.2.

The existing step length estimation methods (i.e. Weinberg, constant step length and with height input) will be used to compare with the proposed solution. The Weinberg approach particularly, requires the acceleration maximal and acceleration minimal for computation according to equation (3) in Chapter 2. Therefore, when a true step is detected from the step detection algorithm, the peak value is assigned to the acceleration maximal and the valley value is assigned to the acceleration minimal in the Weinberg approach computation.

4.5 Compute coordinate using trigonometry function

The calculation of the coordinate is performed for every true step detected by using the trigonometry function; using the heading orientation and step length estimation values as input to the equation below;

$$S_n = S_{n-1} + L_n \begin{bmatrix} sin\ \theta_n \\ cos\theta_n \end{bmatrix} \qquad (5)$$

where S_n is the coordinate of the pedestrian, L_n is the estimated step length and θ_n is the estimated heading orientation of the pedestrian at time step *n*. The first step of the user is relative to the starting position and the following steps is relative to the step before it.

4.6 Fusion between PDR and Wi-Fi fingerprinting IPS

The fusion between PDR and Wi-Fi fingerprinting IPS takes place when PDR is unable to confidently provide user's location. In other words, when the PDR drift errors are large. An example of scenario is tested in this work whereby we detect when the user is not walking in a straight line (i.e. heading orientation is greater than 35 degrees consecutively for more than 3 steps). The algorithm for this scenario detection is shown in Figure 4.3.

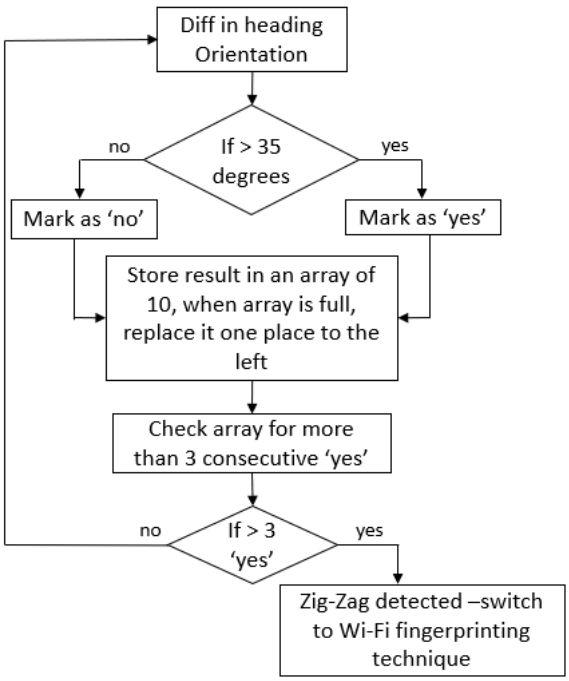

Figure 4.3 Algorithm for zig-zag scenario detection.

Figure 4.3 explains on the zig-zag scenario detection. When the scenario is detected, the system will switch to Wi-Fi fingerprinting-based IPS and reset all of the PDR stored coordinates. In this Wi-Fi fingerprinting technique, it acquires the position estimation by comparing the current recorded Wi-Fi RSSI value with those stored in the fingerprint database. As aforementioned, the k-NN algorithm is used measured by a distance function; Euclidean distance. An example of k-NN classification that is implemented in this work is as shown in Figure 4.4.

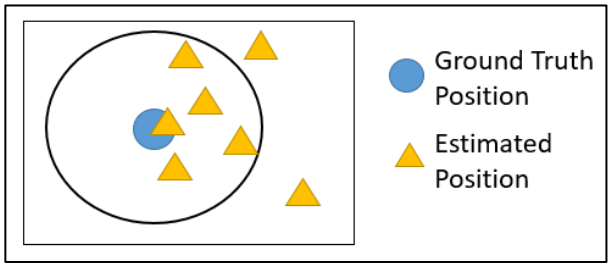

Figure 4.4 k-NN classification implemented.

In this work, the *k* value in the k-NN algorithm is set at $k = 5$. The value of *k* determines the number of possible position estimations that are accepted. From Figure 4.4, the circle represents the ground truth position of the step taken by pedestrian. Meanwhile, the triangle represents the possible position estimation calculated using Euclidean distance function between the measured Wi-Fi RSSI values and the fingerprint database.

When the user is within a correction point proximity, the system will switch back to the PDR-based IPS and take the location of the correction point as the starting point of the PDR.

4.7 GreyZone model: A Proposed Method to Evaluate IPS

After the design of the research methodology, another issue that is discovered is the lack of a standard benchmark for measuring the accuracy of IPS. In conjunction with our literature review in Chapter 2.5, the GreyZone model is introduced.

4.7.1 Issue on the evaluation of the IPS

Positioning systems accuracy measurement often involves 3 dimensional cubes; the longitude, latitude and altitude. As shown in Figure 4.5, depending on the coarse size of the grid and the grid positions, the accuracy of the positioning can be different. All the points are returned results from an IPS, the points fallen inside the ground truth box are considered as accurate results, whereas the points fallen outside the ground truth box are considered inaccurate. Some of the existing work even repeated their experiments in a circle-shaped trajectories (Colombo *et al.*, 2013) to better capture the performance of the system in terms of accuracy, repeatability and robustness, however, similar problem still persist when the centroid of the circle moved and when the size of the circle changes.

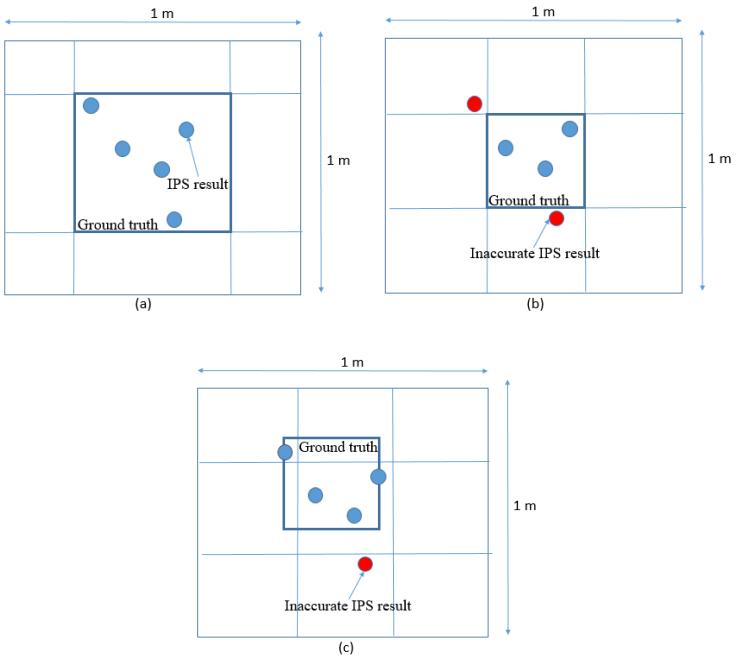

Figure 4.5: The accuracy measured using 2 dimensional grid is affected by the size of the grid; compare the difference between (a) and (b). Figure (c) shows that accuracy can be different when the position of the ground truth is shifted.

4.7.2 The Proposed Solution

In this work, we proposed the GreyZone *(Gz)* model, to model the IPS accuracy using one dimension to reduce such ambiguity. The accuracy metric is represented by $\alpha = Gz(d)$, whereby α is the maximum width of the GreyZone and d is the total distance between the IPS reference point and the IPS measuring point. Figure 4.6 shows an overview concept of the proposed GreyZone model. Specifically, the word GreyZone indicates that the zone in which the developed IPS could not provide a determined location for more than 99% of the time. In other words, for every horizontal path, d, experimented, the accuracy metric is determined

by the maximum width expansion for the GreyZone, α. The smaller the value of α, the higher the accuracy of proposed IPS.

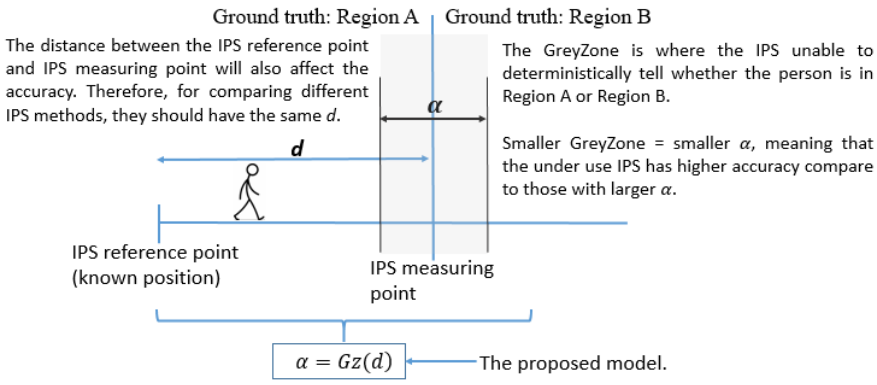

Figure 4.6. The overview concept of proposed GreyZone model.

In order to obtain the GreyZone, α, value of an IPS, firstly, the distance between the IPS reference point and the measuring point, the value d is set as shown in Figure 4.6. Starting from the reference point to the measuring point is considered as Region A and from the measuring point thereafter is considered as Region B. A reference point is a point where an IPS refers when to compute its position. Therefore, it can be Wi-Fi access points, RFID tags, light source (to experiment on light intensity sensor) and also audio source (to experiment on audio sensor) or even the starting point for the PDR technique. To get the maximum width expansion of GreyZone, a condition must be met; when all of the captured walking steps walked from Region A to Region B are detected to be at least 99% correct in their respective regions.

When two or more reference points are used, the GreyZone model accuracy metric will be revised as follows;

i. If the reference points are deployed on the same side as shown in Figure 4.7, the GreyZone method will start from the nearest reference point towards the measuring point as distance in d_1. Then, the proposed GreyZone model accuracy metric will be revised to α =$Gz(d_1) + Gz(d_2)$.

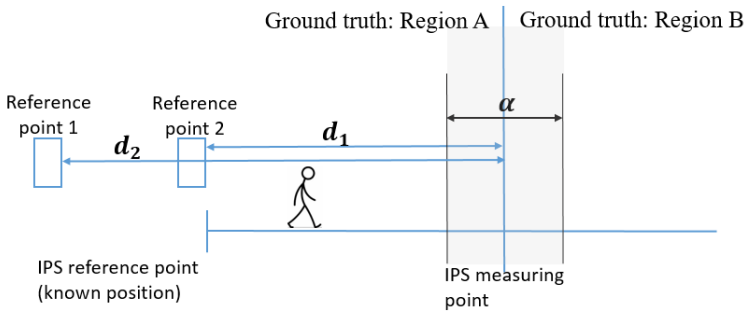

Figure 4.7. When more than one reference points used and deployed on the same side.

To carry out the experiment, the user is required to walk from the direction of reference point 1 towards reference point 2 and not the other way round. The proposed model is the model that is easy to understand and it can provide an abstraction to the test environments. IPS with better positioning accuracy and precision will be able to produce narrower GreyZone. For example using the GreyZone model $\alpha = Gz(d)$, IPS method A model is 4m=Gz(12m) and IPS method B model is 3m=Gz(20m). From the models, IPS method B has better accuracy compared to IPS method A as it can provide smaller GreyZone. IPS method B

is superior because its accuracy can outperform IPS method A even when its distance is 8m further than IPS method A.

4.8 Summary

This chapter has discussed on the implementation of the research methodology. Firstly, PDR based IPS is constructed through an android application by gathering sensors data from the smartphone. Then, for every step detected, the step length estimation and heading orientation estimation are computed. At the same time, Wi-Fi RSSI of all detected APs are also recorded and stored in the fingerprint database which reduces the challenges in manual collection and maintenance of the fingerprint database in Wi-Fi fingerprinting technique. With the computed data, the position estimation is then calculated based on the equation (5) in Chapter 4.5.

Fusion provide switching from PDR to Wi-Fi fingerprinting based IPS when PDR is unable to confidently provide user's location due to large error drift. In the Wi-Fi fingerprinting technique, k-NN algorithm is used for position estimation.

This chapter also presents the implementation of the GreyZone model which is a proposed method to evaluate IPS. As aforementioned in Chapter 2.5, the lack of a standard benchmark makes it hard for researchers to validate and improve on existing works. The proposed GreyZone model can provide an abstraction to the test environments whereby the experiments and verification test at other locations can be easily constructed.

CHAPTER 5

EXPERIMENTAL CONDUCT AND RESULTS

5.1. Experiment conduct and set up

This chapter presents an experimental set up and discussions on the proposed solution. In total, there are four experiments involved. The purpose of each experiments are as follows:-

Table 5.1 Purpose and conclusion of four experiments conducted.

Experiment	Purpose	Conclusion
1	Evaluate Wi-Fi locking speed at various RSSI strength.	It shows that locking speed is faster when we only detect RSSI stronger than a particular threshold compare to detect RSSI with a minimum and maximum bound.
2	Adjustment and improvement on overall PDR map.	Through a single mode of correction point detection, the PDR map can be adjusted and overall accuracy is improved.
3	PDR correction via recalibration using a pair of correction points.	Experiments were tested on three heterogeneous smartphone models as well as five different users. An improvement of 50% in positioning accuracy were shown in proposed solution.

4	Wi-Fi fingerprinting map through PDR map.	It is possible for proposed solution to be used to create and maintain the fingerprint map of a building.

Throughout the whole experimental conduct, Intel Edison boards are deployed in the building as correction points.

5.2. Experiment on Wi-Fi locking

This experiment was conducted by recording the Wi-Fi RSSI locking time based on different ranges of RSSI values set. The result is shown in Figure 5.1.

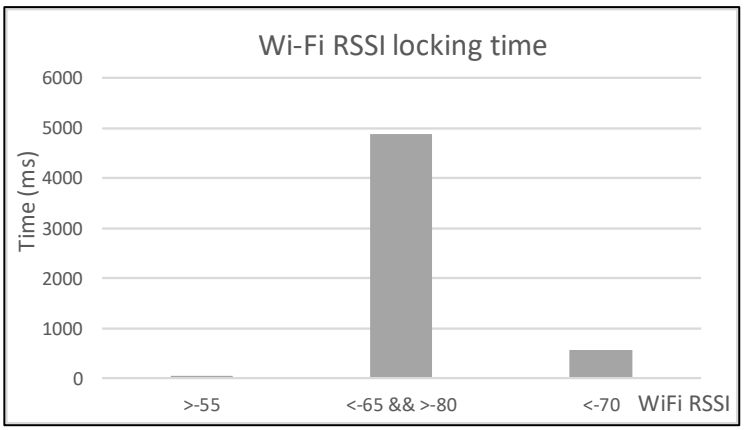

Figure 5.1. Wi-Fi RSSI locking time on different ranges of RSSI set.

Figure 5.1 shows the average Wi-Fi RSSI locking time recorded at different ranges of RSSI values set. The term locking time in this experiment represents the time taken for smartphone to detect the Wi-Fi RSSI ranges set. According to Figure 5.1, the lowest locking time recorded is at RSSI range greater than -55 dBm while the highest locking time (longest time taken to detect RSSI range) is recorded when RSSI is set at a range between -65 dBm and -80

dBm. This experiment proves that our proposed solution through correction points can indeed improve Wi-Fi locking time when they are set to be detected within sub-meter. As such, the correction points are acting as an A-GPS for quick detection and simultaneously correct the position at a shorter time.

5.3. Experiment on adjustment and improvement on PDR map

This experiment is conducted to show the adjustment and improvement on the drift of PDR map when a single correction point is detected. The experiment is set up as shown in Figure 5.2 where five correction points are deployed with known location. PDR map is constructed when pedestrian walked from the starting point at correction point 1 (CP1) to correction point 5 (CP5) according to the dotted arrows in Figure 5.2. A total of four walking trials are repeated. The results in Figure 5.3(a) and Figure 5.3(b) show the PDR map before and after adjustment is made on each four trials respectively.

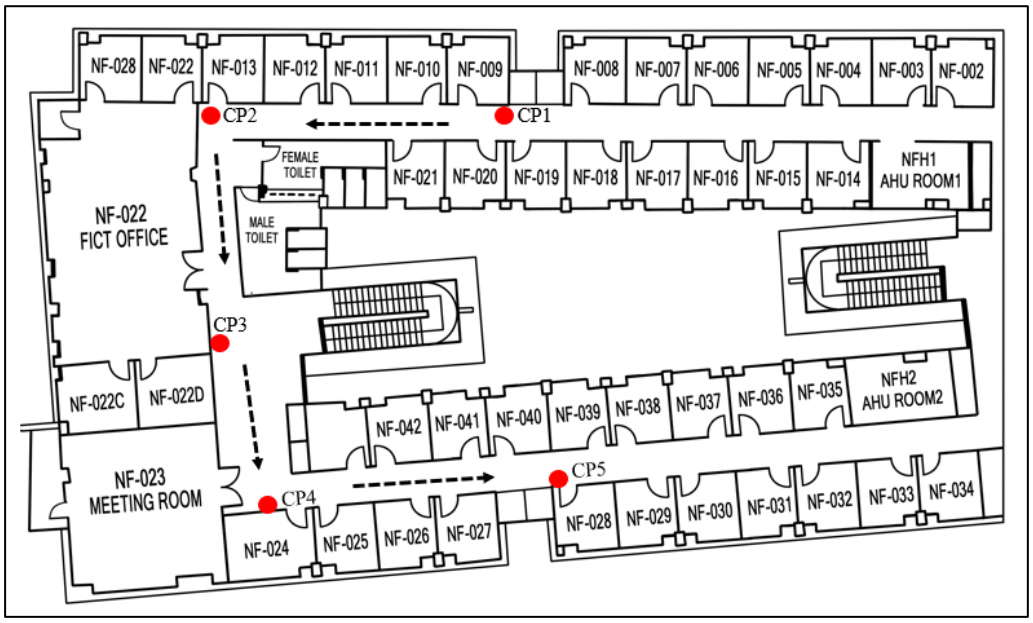

Figure 5.2. Experimental set up with five correction points deployed.

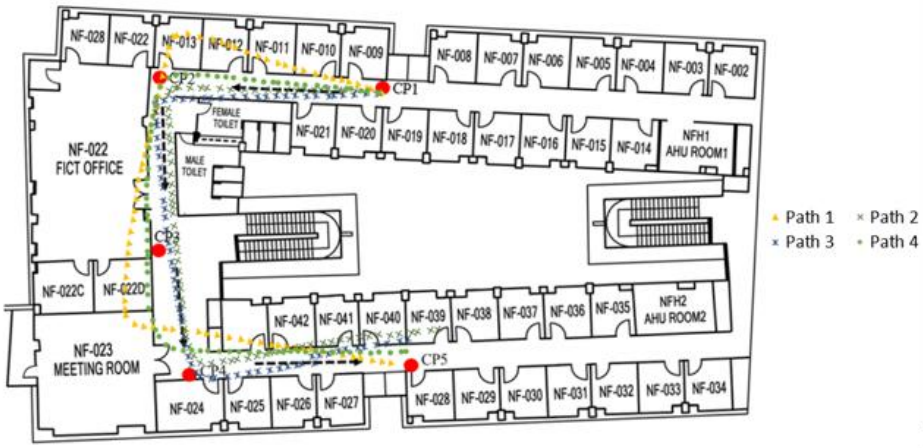

Figure 5.3(a). PDR map before adjustment.

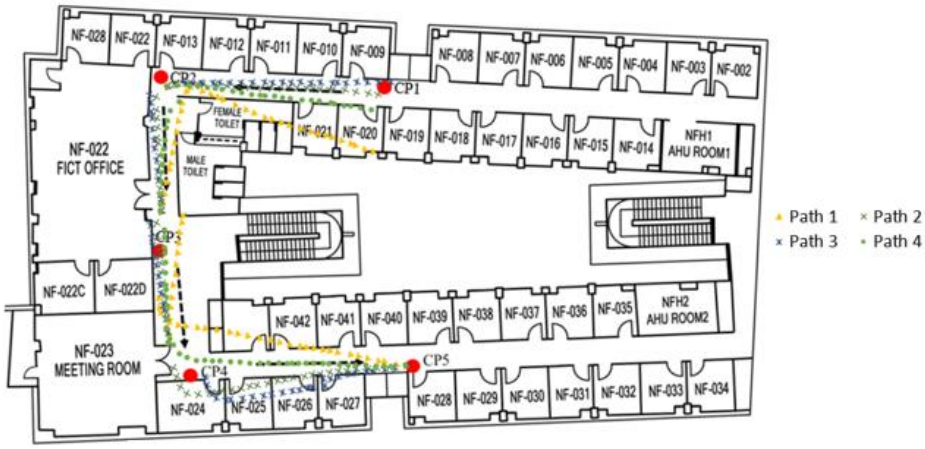

Figure 5.3(b). Adjusted PDR map.

By merging the PDR map on the floor plan in Figure 5.2, the PDR map adjustment can be observed in Figure 5.3(a) and 5.3(b). In Figure 5.3(a), the tracked PDR map shows great drift error from the original path while in Figure 5.3(b), with the help of correction point's detection, the overall drift error is improved. The path shown in Figure 5.3(b) is more concentrated on the walkway and not drifted into the rooms such as in Figure 5.3(a).

5.4. Positioning accuracy of proposed PDR recalibration compared with existing works using the GreyZone model

The PDR recalibration experiment is set up as shown in Figure 5.4(a) and Figure 5.4(b). Figure 5.4(a) is set up for the conventional PDR approach with different step length estimation methods from the existing works (i.e. constant, height input and Weinberg) for comparison with our proposed PDR recalibration. Figure 5.4(b) is set up for our proposed PDR recalibration.

Hence, the GreyZone accuracy metric for the experiment in Figure 5.4(a) is $\boldsymbol{\alpha = Gz(d)}$ while the GreyZone accuracy metric for our proposed PDR recalibration will be revised to $\boldsymbol{\alpha = Gz(d_1) + Gz(d_2)}$ as aforementioned in Chapter 4.7.2 and as shown in Figure 5.4(b). The distance between the correction points (i.e. the correction point 1 to the correction point 2) is set to be 10m. Then, distances, d and d_1 are set and tested to a variation of 10m, 20m, 30m and 40m. Evaluations were also done on 5 pedestrians (4 males and 1 female), each on different smartphone models; Smartphone S6, Samsung S3 Mini and One Plus 3T. Experimental results are shown in Figures 5.5, 5.6(a) and 5.6(b).

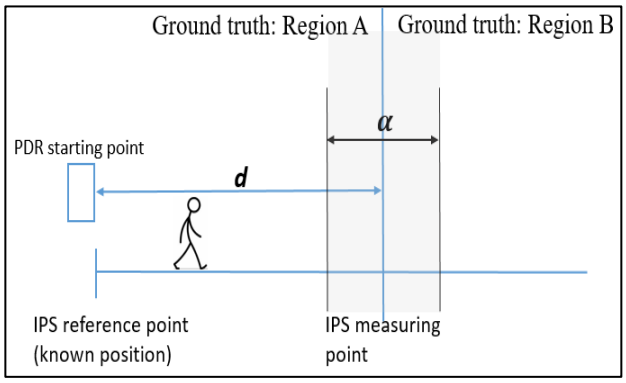

Figure 5.4(a). Experimental set up for the conventional PDR based IPS.

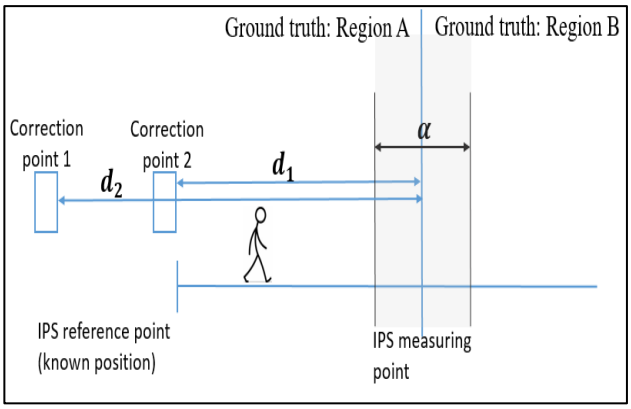

Figure 5.4(b). Experimental set up for proposed PDR based IPS with PDR recalibration.

Table 5.2. Mean distance error of five pedestrians observed in Samsung S6 smartphone at increasing distances.

	Distances, d_1			
	10m	**20m**	**30m**	**40m**
Weinberg	4.47	9.24	13.11	17.47
Constant step length	1.64	2.83	4.66	6.14
With height input	1.51	2.62	3.72	4.81
Proposed solution with correction points	0.72	1.20	2.34	2.71

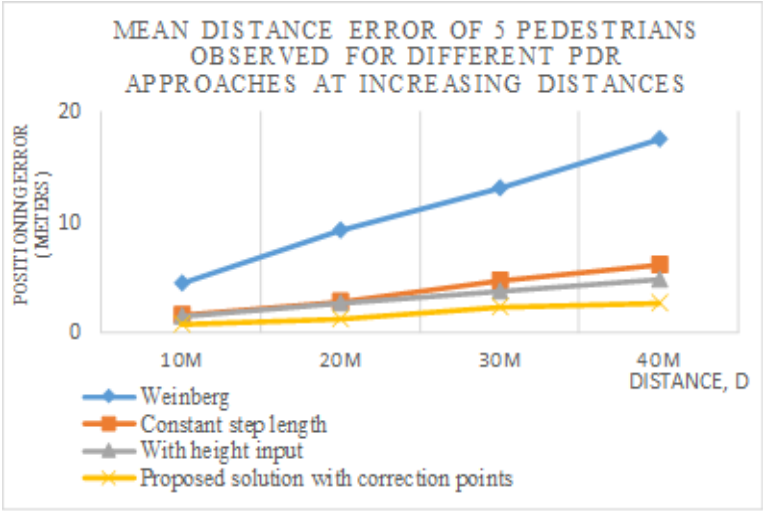

Figure 5.5. Graph of mean distance error observed for different PDR approaches in Samsung S6 smartphone.

Table 5.2 and Figure 5.5 show the results of absolute mean distance error observed for different PDR approaches in only Samsung S6 smartphone at increasing distances experimented. As PDR approach uses previous location to estimate for current pedestrian's location, PDR suffers from error accumulation as the distance increases. For instance, the step length estimation with height input shows 4.81m of positioning error after travelling for 40m. Our proposed PDR recalibration has the lowest error accumulation, wherein after travelling for 40m, the positioning error is reduced to 2.71m compared to other PDR which uses different step length estimation approaches. Overall, the positioning accuracy of the proposed solution showed 50% improvement compared to the next best method of step length estimation (i.e. with height input).

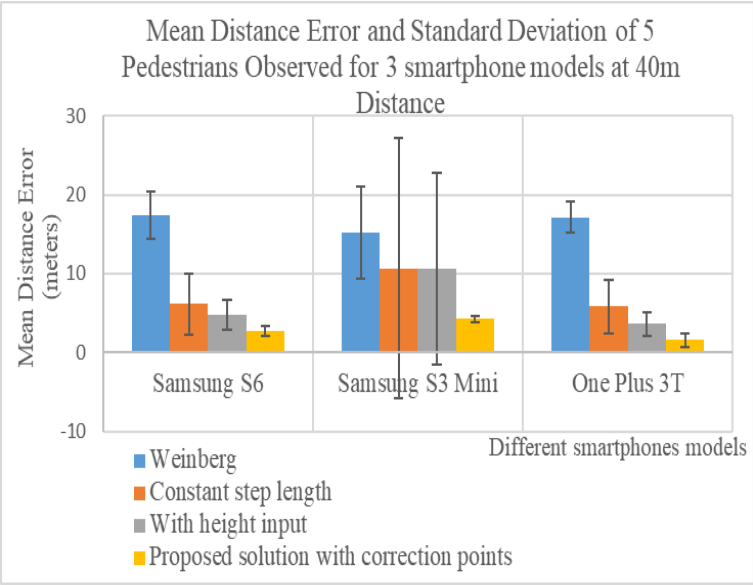

Figure 5.6(a). Mean distance error observed for three different smartphone models used by five different pedestrians at 10m distance.

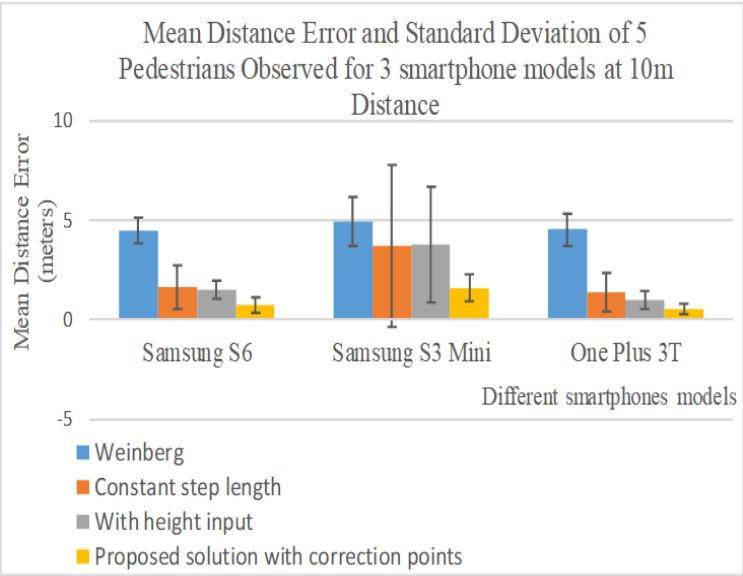

Figure 5.6(b). Mean distance error observed for three different smartphone models used by five different pedestrians at 40m distance.

Figure 5.6(a) and Figure 5.6(b) show the mean distance error using three different smartphones after travelling 10m and 40m distance respectively. From the experiment result, it is important to note that the distance error is affected by

heterogeneous smartphone models and different users' walking gaits. This experiment also shows that the proposed PDR recalibration is able to reduce the distance error more than 50% compared to the other PDR techniques. This work shows that PDR based IPS calibrated with the proposed correction points can estimate distance travel more accurately and the users can travel further before error becomes significantly large.

The candlestick on Figure 5.6(a) and Figure 5.6(b) show the standard deviation of our experiment. This experiment also shows that the proposed PDR recalibration has the lowest standard deviation in every smartphone tested ranging from 0.4 to 0.8 compared to other PDR approaches. In other words, the proposed PDR recalibration provides a consistent positioning among not only heterogeneous smartphone models but also among variation of pedestrians.

5.5. Experiment on Wi-Fi fingerprinting mapping through PDR map

This experiment is conducted to show the use case of adjusted and improved PDR map. Wi-Fi signals at the corridor are fingerprinted by recording the RSSI when the user performs PDR positioning. IPS trials in Figure 5.7 represent the attempts to perform indoor positioning using Wi-Fi fingerprinting technique. The fingerprint database in the offline phase of Wi-Fi fingerprinting technique is generated using the proposed PDR map as mentioned in Chapter 4.3.3.

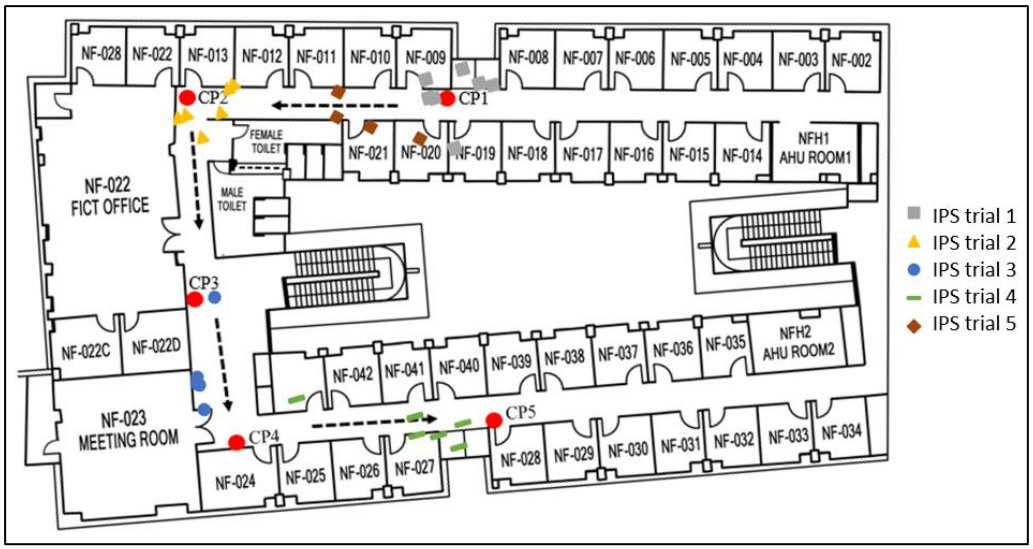

Figure 5.7. Various IPS trials of Wi-Fi fingerprinting position estimation using PDR map generated by the proposed solution.

Figure 5.7 shows the estimated position of smartphone using Wi-Fi fingerprinting approach based on the Wi-Fi fingerprint map generated using the proposed PDR approach. From Figure 5.7, it is observed that the position estimation clustered around a certain correction point when it is detected nearby, for example, in IPS trial 1 to IPS trial 4 while IPS trial 5 shows a wider range of possible position estimation when position estimation is expected within CP1 and CP2. This experiment shows that it is possible to use the proposed solution to create and maintain Wi-Fi fingerprint map of a building.

On the other hand, this experiment also shows that PDR based IPS is able to provide continuous position tracking which it is not possible with Wi-Fi fingerprinting technique. This is because the RSSI value fluctuates, hence, it is difficult to uniquely distinguish each step with Wi-Fi fingerprinting.

5.6. Summary

This chapter has covered the experiment conducts and results on the proposed solution. A total of four experiments are conducted. The first experiment on evaluating the Wi-Fi RSSI locking time shows that by reducing the region for correction point's detection to sub-meter, it allows for quick detection from the smartphone and simultaneously correct the position at shorter time. The result from the second experiment on a single correction point detection provide adjustment and improvement in the overall accuracy of the PDR map. Third experiment is conducted on the recalibration of PDR's step length estimation through a pair of correction points. The positioning accuracy is compared with existing step length estimation approaches (i.e. Weinberg, constant and with height input). The proposed solution is able to reduce the distance error to more than 50% when compared with the other approaches mentioned. The fourth experiment is conducted by adopting PDR map to be used as Wi-Fi fingerprint map. The result proves the possibility to conduct Wi-Fi fingerprinting based IPS through the Wi-Fi fingerprint map that is adopted from the proposed PDR map.

CHAPTER 6

CONCLUSION AND FUTURE WORK

6.1. Conclusion

This research has developed a more accurate IPS that is able to perform continuous position tracking without using additional hardware to be attached on a smartphone. This research presents some existing approaches that require additional hardware to be attached on the smartphone but we opined that such implementation can be inconvenient for users. Therefore, IPS techniques like Wi-Fi fingerprinting and PDR are further discussed because almost every smartphone has Wi-Fi module and equipped with various sensors for PDR such as accelerometer, magnetometer and gyroscope. These sensors are becoming de-facto standard sensors on modern day smartphones.

This work has showed that although the Wi-Fi fingerprinting technique requires no additional hardware, the fluctuations of RSSI are not suitable for continuous position tracking. In addition to that, the disadvantages are also extended to heterogeneous smartphone models as well. Hence, this work has developed a PDR-based IPS for its ability to provide continuous position tracking as the position is estimated for every step detected by the user. Unfortunately, the PDR technique suffers from error accumulation over time. Positioning accuracy of the PDR technique is also affected by heterogeneous smartphone models' sensors as different smartphone may use different sensors and different users have different walking gaits.

Therefore, this work introduces the concept of correction points to improve the overall accuracy of PDR. Our proposed correction points are different from the existing beacons based solutions because the proposed correction points not only allow adjustment on the current position but also perform recalibration on smartphone measurements (i.e. step length estimation) to improve the positioning accuracy of subsequent PDR positioning. As such, the proposed IPS solution will work on different smartphone models and different users with different step lengths and walking gaits.

Furthermore, our proposed solution can be used to perform the collection of W-Fi fingerprint while the user is using PDR-based IPS. This solution greatly reduces the effort for manually collect and maintain the fingerprint database from time to time, which is required by Wi-Fi fingerprinting based IPS. With this, the fusion of PDR and Wi-Fi fingerprinting based IPS is develop. The fusion provides switching from PDR to Wi-Fi fingerprinting IPS when PDR is unable to confidently provide the user's location due to large error drift. In this case, we are able to have another IPS (i.e. Wi-Fi fingerprinting-based IPS) to function under those circumstances to allow good user experience.

While the proposed solution has been devised, another issue is discovered; to compare the IPS accuracy with the existing works and different approaches. The existing works evaluated their positioning accuracy in vastly different ways, using different test environments. According to Adler *et* al. (2015), there is no standard benchmark to measure the IPS accuracy which makes comparison with the existing works a very challenging issue. In order to tackle the mentioned issue, a novel method for measuring and comparing the

effectiveness of various IPS through a modelling technique; referred to as the GreyZone model is introduced. This model provides an abstraction to the test environment so that the experiments can be easily reconstructed and the verification test at other locations is made possible.

The experiments conducted in this research consist of four parts. Firstly, the experiment on the deployment of correction points to be detected within its sub-meter proximity were conducted. By reducing the proximity for detection towards sub-meter, the correction points act as A-GPS (a system that often significantly improves the TTFF of the GPS-based positioning system) that improves the time taken for detection and simultaneously make the correction needed as signals fracture at further distance.

Secondly, with the detection of a single mode of correction point, the PDR map is adjusted and improves the overall accuracy of PDR based IPS. This experiment has satisfied the first objective in this research which is to develop a PDR based IPS solution that enables continuous position tracking and improving the positioning accuracy.

Then, as proposed, with a pair of correction points detection, recalibration towards the step length estimation are observed and improvement in positioning accuracy is recorded at 50% when compared to the conventional PDR technique. Hence, this experiment fulfill the second objective in this research which is to design efficient approach for PDR based IPS that is able to provide improvement in positioning accuracy when tested on heterogeneous smartphone models and various users with different walking height and gaits.

Last but not least, the experiment done on Wi-Fi fingerprinting mapping through the PDR map shows that the proposed PDR map can reduce the challenges in manual collection and maintenance of the Wi-Fi fingerprint database. Through this experiment, the fusion also allows switching from PDR to Wi-Fi fingerprinting technique when PDR is unable to provide user's location due to large drift error. Hence, it satisfies the third objective in this research.

6.2. Future Work

As for future work, the proposed solution can be extended to detect multi-floor positioning by using other sensor to detect the atmospheric pressure or by using correction points for multi-floor detection. Besides, the proposed solution can also combine with existing outdoor positioning system (i.e. GPS) to showcase a full indoor-outdoor positioning system.

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