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動態調整 IMU 並結合 Wi-Fi 資訊強化室內定位效果

A Dynamic Approach to Fusing IMU and Wi-Fi for Improving Indoor Positioning Accuracy

許林民

Lin-Ming Hsu

指導教授：陳健輝 博士
　　　　　吳曉光 博士

Advisor: Gen-Huey Chen, Ph.D.
　　　　 Eric Hsiao-Kuang Wu, Ph.D.

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本論文係 **許林民** 君（學號R98922084）在國立臺灣大學資訊工程學系完成之碩士學位論文，於民國 100 年 7 月 29 日承下列考試委員審查通過及口試及格，特此證明

口試委員：

陳健輝

（指導教授）

林俊宏　　吳曉文

蔡子傑　　周承復

系　主　任　呂育道

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中文摘要

利用短距離無線技術(例如無線區域網路)來做室內定位系統已經被廣泛的研究，額外的資訊例如新興、便宜的微機電系統或是圖資也被用來增進室內定位的精準度。雖然很多將無線區域網路定位系統與微機電系統結合的方法很多，但他們假設使用者知道起始點跟方向，這樣的資訊並不是在任何情況下都可以容易的取得。因此，我們提出了一個室內定位系統來解決這個問題，同時也增加定位的精準度。在這篇論文中，我們將展示我們如何不一樣的利用粒子濾波將無線區域網路定位系統與微機電系統整合來提供行人追蹤的服務。我們將三種整合後會產生的問題進行妥善的處理，起始位置的問題、累積誤差的問題以及無線區域網路定位系統不穩定的問題。我們在南港展覽館四樓進行系統的評估，其結果與只使用指紋式無線區域網路定位系統以及粒子濾波方法，其效果都有顯著的提升。此外與直接將無線區域網路定位系統與微機電系統結合的方法相比也有不錯的表現，我們分別在三種不同的測試路徑上分別有 206%、203%以及 159%定位精準度的提升。

關鍵字 – 慣性定位, 指紋式定位, 粒子濾波, 地圖濾波, 室內定位系統.

ABSTRACT

Indoor positioning systems based on short-range wireless technologies such as wireless local area network (WLAN) have been widely investigated. Additional information produced by the emerging low-cost micro-electro-mechanical system (MEMS) sensors or floor plans is usually used to improve the accuracy of indoor positioning system. Although several combining WLAN with MEMS based inertial measurement units (IMU) researches have been researched, they assume the user's initial location and heading is given. But this information might not be available in some circumstances. Therefore, we proposed an indoor positioning system to solve such problem as well as improving the positioning accuracy. In this thesis, we show how to differently fuse IMU, map information and Wi-Fi by the utilization of particle filter to provide indoor pedestrian tracking service. Three drawbacks from Wi-Fi fingerprinting and IMU are handled which are the initial location problem, drift error problem and the unsteadiness of Wi-Fi positioning. The accuracy of the fused system was evaluated in Taipei NanGang Exhibition Center against ground truth. Our results show that accuracy is much higher than Wi-Fi fingerprinting alone and particle filter. Furthermore, we achieve better performance than fusing IMU and Wi-Fi fingerprinting directly. Up to

206%, 203% and 159 % enhancement are achieved in three distinct test paths respectively when compared with the latter approach.

***Keywords* –** IMU, fingerprinting, particle filter, map filter, indoor positioning system.

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Chapter 1

Introduction

In modern society, indoor localization and navigation is essential and inevitable, and it makes our life more convenient and comfortable. By the aid of indoor localization and navigation [1-22], a work of art could be found easier in a museum, more people could be saved in a scene of a fire by firefighters, and the blind could be guided more accurately. However, researchers have encountered difficult navigation problems in indoor environment.

Global Positioning System [23-25] has been widely used in outdoor environment and it is installed in several devices, such as smart phones, car navigator…etc. However, the accuracy of GPS positioning degrades seriously in indoor environment, their signals are either blocked or poorly received. Although High Sensitivity (HS) receiver could be utilized to detect weak GPS signal for positioning, the signal is still not reliable due to errors such as multipath [26].

In recent years, a lot of mechanisms were used for indoor positioning including radio-frequency identification (RFID) [7], ultra-wideband (UWB) [27], infrared [1, 13], ultrasound [5], vision [28], radio map based Wi-Fi positioning [18], inertial measurement units (IMUs) based on MEMS (Micro Electro-Mechanical Systems) and many others [12]. Radio-frequency identification [7] is used to assist indoor pedestrian navigation by providing absolute position information to the navigation system, but the cost is expensive. There are usually a lot of rooms in a typical building which increases the expense of cost to add these in each room. Furthermore, maintenance is another costly issue. Different type of mechanisms such as ultra wide band (UWB) [27] can be used as well but they are strongly influenced by radio signal interaction with environments.

Of all approaches above, radio map (fingerprinting) based Wi-Fi positioning is the most popular way because Wi-Fi signals are everywhere in modern buildings, while the other mechanisms cost more in environment setup. Nevertheless, radio map based Wi-Fi positioning does not perform well in a wide and empty place. In such a place, the differences of the signal strength of an AP received by the neighboring reference points are too small to distinguish. In order to improve the accuracy in such environment, some other techniques should be exploited and combined with radio map based Wi-Fi positioning.

Inertial Measurement Units (IMUs), which is based on MEMS (Micro Electro-Mechanical Systems), have become more and more desirable. Expansive, heavy and high-accuracy IMU has long been used by airplanes and ships for route guidance and positioning. As a result of rapid development of technologies, there are also IMU devices which are smaller and cheaper but less accurate. In recent years, low-cost IMU has been commonly integrated in navigation systems, such as Inertial Navigation Systems (INS) [29], to improve the positioning accuracy. By the aid of IMU, a navigation system can supply continuous positioning, heading and velocity estimation. However, a main disadvantage of using IMU for navigation is that they suffer from accumulated error. Because the navigation system is continually adding detected changes to its previously-calculated locations, any small errors in measurement are accumulated from time to time. This leads to drift from the actual location [30].

To avoid drift error, several significant research efforts were presented. The research in [19] engaged in building human movement characteristics models which successfully distinguish the actions like walking, running, walking a circle, stair ascent and descent, and sit-to-stand and stand-to-sit. Some filtering methods were used to decrease drift error. Particle filter was used to find out the object's position by approximating the dynamic system's probability density function (pdf) through generating a set of samples with and without the support of map information [2, 3, 9, 14, 31]. In [2], particle filtering was utilized in application where Wi-Fi and INS are both used. Combining these two different positioning technologies leads to interesting results due to their heterogeneous but complementary characteristics – INS has the advantage of high availability, high data rate, and it is not easily effected by external noises but fast accumulative error, while Wi-Fi positioning rate is comparably low and susceptible to external noises yet the positioning errors are bounded.

The systems mentioned above [2, 3, 9, 14, 19, 31] all have a strong assumption: the starting point and the moving direction must be given [32] . If the starting point and the moving direction are given, their algorithms perform well. However, the starting point and the moving direction are not always available for a navigation system, such as the navigation system for the blind. It is not unreasonable to ask the blind to input his/her position first then he/she could use the positioning system.

In this thesis, we proposed an algorithm that combines Wi-Fi fingerprinting system and IMU to solve the problem that starting point and the moving direction are necessary when positioning. First, an algorithm, named Modifying Outset and Direction Approach (MODA), which uses the historical positioning data obtained by Wi-Fi and IMU systems to determine the starting point and the initial heading of the navigation, is proposed. In MODA, the initial heading is estimated by calculating the linear regression line from the Wi-Fi points. Then we use the total walking distance from IMU to approximate all the possible walking area starting from Wi-Fi points. The user is expected near the edge of every walking area, so a minimum estimation function is proposed to evaluate the starting position of the user. Once we have outset position and initial heading, we could infer the current position of the user by absolutize the recorded path from IMU. After we pre-processed the Wi-Fi and IMU data which are done by

MODA, we use this information to further update the probability of density function in particle filtering rather than using them directly [2]. The accuracy of the fused system was evaluated in Taipei NanGang Exhibition Center against ground truth. Our results show that accuracy is much higher than Wi-Fi fingerprinting alone and we achieve better performance than fusing IMU and Wi-Fi fingerprinting directly. Up to 206%, 203% and 159 % enhancement are achieved in three distinct test paths respectively when compared with the latter approach. The followed chapters are arranged as below. In the next Chapter we will describe the related works, especially the fusion of WLAN and INS. Our algorithm MODA Particle Filter will be presented in Chapter 3. The experiments and discussion are given in Chapter 4. Finally we summarize the thesis in Chapter 5.

Chapter 2

Related Work

This chapter gives a brief overview of different approaches for radio map (fingerprinting) based wireless LANs positioning and particle filter based tracking mechanisms. The fingerprinting based approach (e.g., KNN) and particle filter based approaches are implemented to compare the performance of the proposed tracking system.

2.1 Fingerprinting Based Positioning System

Fingerprinting based positioning approach is divided into two phases: offline phase and online phase. In offline phase, the received signal strength (RSS) values from different access points (Aps) are gathered by a device at predefined places, which are named reference points (RPs) to establish a fingerprint database. During online phase, the user collects RSS values at an interested position then these RSS measurements are used to compare with the fingerprint database in order to estimate the user's location.

A commonly used approach named K-nearest neighbor (KNN) [18], which calculates the Euclidean distance on RSS space between RSS values of the RPs and observed RSS values to estimate the user's location. K RPs that have smallest distances are chosen to estimate the current position.

However, as a result of radio propagation depending heavily on the unceasingly changing environment, the accuracy of this kind of system is restricted and sometimes the fluctuation of signal strength cause many unexpected jumps in terms of an approximated faraway position from the real one.

2.2 Particle Filter Based Tracking System

The particle filter is a sequential Monte Carlo method that generates random samples, also known as particles, based on a measurement model and estimates their probability distributions [33, 34]. Furthermore, the particle filter can be deployed in non-Gaussian and non-linear models. Providing absolute position by combining inertial measurement units with particle filter has been researched [2, 9, 16, 22, 35]. This sort of systems could be roughly divided into two groups based on the availability of knowledge of initial position and orientation. Non-autonomous tracking systems are those who assume the information of initial location and heading is given while autonomous tracking systems do not require such information.

2.2.1 Non-autonomous tracking systems

In [22], the tracking accuracy is improved by using the information acquired from inertial measurement units (IMUs) to revise the measurement model and thus the filter could generate more applicable particles. In virtue of the convenience of internet, the maps of all the public buildings are available in digital format online. Additional map information can be used to improve the performance of particle filter by assigning impossible particles zero weights, such as those bump into the wall [36, 37]. Backtracking based on the map information is also proposed in [9]. In [2], they proposed a WLAN-INS fusion algorithm for pedestrian navigation based on particle filter. The inertial signals are used to count steps and the length of step as well which is then fused with WLAN position. This approach also exploits map information to constrain the particles or, to put it differently, to eliminate those particles having impossible trajectory. However, the major drawback of these methods is that they are non-autonomous. In other words, the initial point and heading must be given.

2.2.2 Autonomous tracking systems

An entirely autonomous tracking system has been proposed in [35]. They preprocessed the building map to a link-node model map. Every corner in the map is referred to a node and if there is a corridor between two corners those two nodes are connected by a line. When the tracking system begins, the set of successive points are transformed into a motion model path in each step. The system uses the motion model path to match the link-node model map to find the possible position. The disadvantage of such system is that the entire map is involved into computation thus the real time positioning is impossible.

Another autonomous tracking system that combines with WLAN is proposed. In [16], the WLAN position is utilized in the beginning to reduce the particles that are scatted over the whole building. The particles are significantly diminished from 4530000 particles to 136000 particles, less than 1/30 of the number that required to stand for the unlimited prior over the thorough building. Although this approach does not need the knowledge of initial point and orientation, the rate of converging particles into one cluster relies mainly on map information and the behavior of the user. The more complicated path the user walk, the faster it converges. The reason is that the complicated path could decrease the ambiguity in an environmental symmetry building. So, if the user's walk style is simple, walking along a corridor for instance, this approach could not converge into one cluster as it wished in some cases thus resulting poor performance. Furthermore, since the initial points are uniformly distributed in a region, the accuracy could be as poor as the region size which might be as large as an access point's coverage area when walking in a broad and long corridor.

2.3 Chapter Summary

From chapter 2.1 and chapter 2.2, we can conclude that there are three problems. The first one is that is we use the fingerprinting based method KNN, we will suffer from the unstable positioning problem which results in the uncertainty to the user. The second problem is that a positioning system should be autonomous. The information of initial position and heading is not always available. Thirdly, the computation complexity should not be high and the speed of convergence should be fast. A real time tracking system should not let the user wait too long.

Therefore, the goal of this thesis is to present a real time and autonomous tracking system which combines WLAN and IMU measurements. In this thesis, the fingerprinting based positioning jumps are eliminated by using particle filter since the particles are far away from those jumps. In addition, computation complexity is reduced by constraining the particles in a region. Because the number of particles are lessened, enormous computational time is saved. Lastly, we find the outset point and initial direction for IMU in each step to ensure that the recorded path from IMU is correctly matched to the map.

In the next Chapter, we present a positioning system that combines an existing WLAN infrastructure with IMU. The initial information is not necessary in our system and the rate of convergence is speeded up by the data fusion of WLAN and IMU. The verification of our positioning system has been shown in Chapter 4.

Chapter 3

Indoor Tracking System

In this chapter we describe our indoor tracking system in four sections. The complete flow chart of our positioning system is demonstrated in Figure 3.1. There are two phases in our system. Offline phase can be deemed as the setup of the tracking system whereas online phase is referred to providing positioning services. As you can see the system is composed of client and server. The client is supposed to collect the measurement of IMU and Wi-Fi RSS. The fingerprinting database needs to be established during offline phase because those data are then used to be compared with online RSS measurements. In chapter 3.1, we first describe the Wi-Fi positioning system we use because there are lots of different Wi-Fi positioning techniques. Right after that in chapter 3.2, we depict how we use the information obtained from IMU devices. In chapter 3.3, we explain how we use the measurements from Wi-Fi positioning and IMU to produce a new possible location. The procedure of MODA is narrated in detail and the flow chart is provided as well. In chapter 3.4, we show how the output of MODA is combined with particle filter and we also illustrate the whole flow path of MODA particle filter in detail.

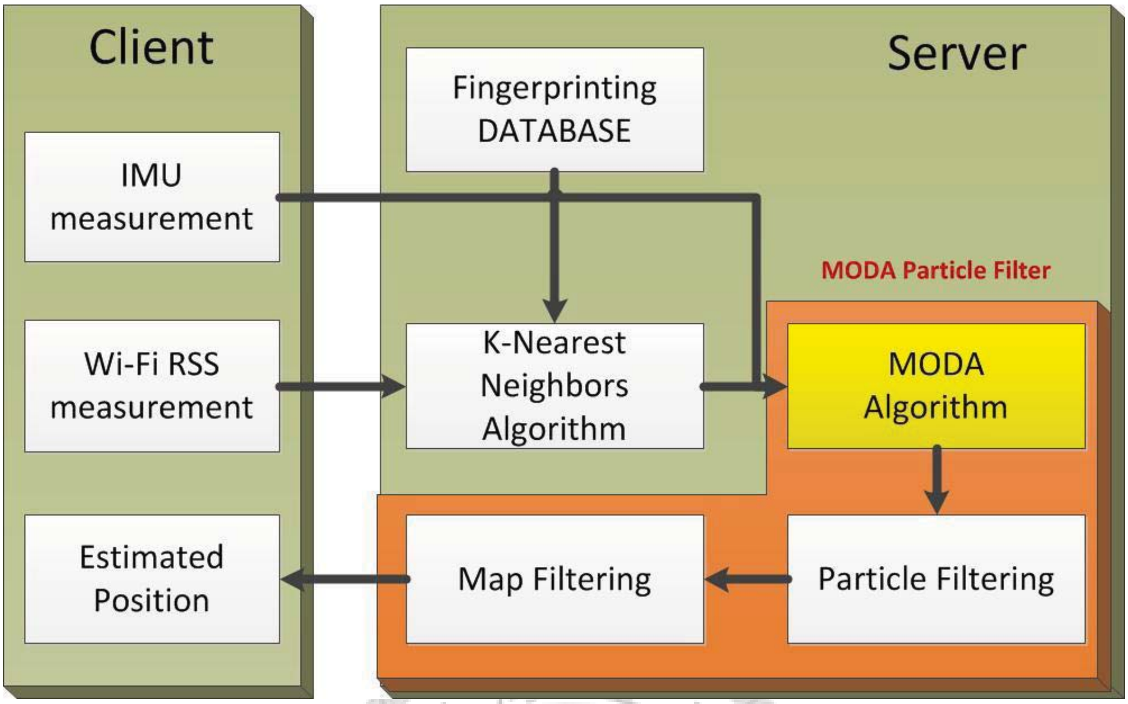


Figure 3.1: Flow chart of our positioning system

3.1 Wi-Fi Positioning System

The most popular network based localization system is Received Signal Strength (RSS) based system, because the RSS value is apparent and available. Based on these observed RSS values, a well-known method called K-Nearest Neighbors (KNN) has widely been used. This algorithm includes two phases.

3.1.1 Offline phase

Offline phase is the training period that allows the system to collect and preprocess received strength signal (RSS) data at the area of interest then these data are used to enable the system to estimate the user's position in the online phase. The first operation we do is to build the fingerprinting database. The RSS value from every access points at each reference points are measured and stored as the characteristics (fingerprint) of the reference points in a database. The position of reference point j is represented as $W_j = (x_j, y_j)$ and the characteristic vector of reference point j is expressed as $V_j = \{RSS_1, RSS_2, ..., RSS_n\}$.

3.1.2 Online phase

In the online phase, assume that there are n access points in this environment. A user equipped with an intelligent device standing at an unknown position collects RSS values from detectable access points, which are then used with the database to estimate the location of the user. When the device receives the RSS values from all access points as an observed vector O, where $O = \{RSS_1, RSS_2, ..., RSS_n\}$,.we calculate the Euclidean distance(in RSS space) between this observed RSS vector O and each reference point j's characteristic vectors. The Euclidian distance is defined in equation (1)

$$d(O, V_j) = \sqrt{\sum_{i=1}^{n} (O_i - V_{j,i})^2} \tag{1}$$

Where $d(O, V_j)$ is the Euclidean distance between observed vector O and the premeasured vector stored in database at reference point j, O_i is the $i-th$ RSS value in vector O, $V_{j,i}$ is the $i-th$ RSS value in vector V_j.Then the member of the possible reference point set N_k is determined as follows in equation (2).

$$N_k = \left\{ \arg\min_{V_j \in \Upsilon} \left[d\left(O, V_j\right) \right] \backslash V_j \notin N_{k-1} \right\} \tag{2}$$

Where Υ is the set of predefined reference points in database.

Finally, the position of the user is calculated as follows:

$$W = \frac{\sum_i^k \left(d\left(O, V_i\right) \bullet W_i \right)}{\sum_i^k \left(d(O, V_i) \right)} \text{ with } W_i \in N_k \tag{3}$$

3.2 Inertial Measurement Units System

There are two IMUs in our system, one is attached on waist, and the other is tied on foot. These two IMUs are equipped with gyroscopes and accelerometers sensors. For convenience, we call the former IMU1, and the latter IMU2. By IMU1, we use the gyroscope to estimate the user's turning angle and the Z-axis of accelerometer to distinguish whether the user is walking. Through IMU2, the information of gyroscope and accelerometer are combined to approximate the step size. Finally, the IMU system outputs a walking vector $\left(I_t^x, I_t^y\right)$, where I stands for IMU, x is the walking distance on x-axis, y is the walking distance on y-axis, t represents the time tag. Noted that the x-axis or y-axis is a relative coordinates, the absolute coordinates is unknown since we have assumed that initial heading and location is unknown.

3.3 Modifying Outset point and Direction Approach

The main idea is that we observe the relationship between the walking path and the Wi-Fi positioning results during the walk. Interestingly, although the Wi-Fi positioning results are not accurate in short term, the long-term tendency of the heading is roughly correct. The reason is despite that fingerprinting-based Wi-Fi positioning is easily influenced by external disturbance which results in unsteadiness, the positioning error is bounded. In virtue of the complementary error feature, combining IMU and Wi-Fi positioning system together is appropriate. MODA fusion structure is demonstrated in Figure 3.2. As you can see, we dynamically modify the outset point and direction trying to find the best path that matches the linear regression function. After that, we use the calculated outset point and direction to infer the current position.

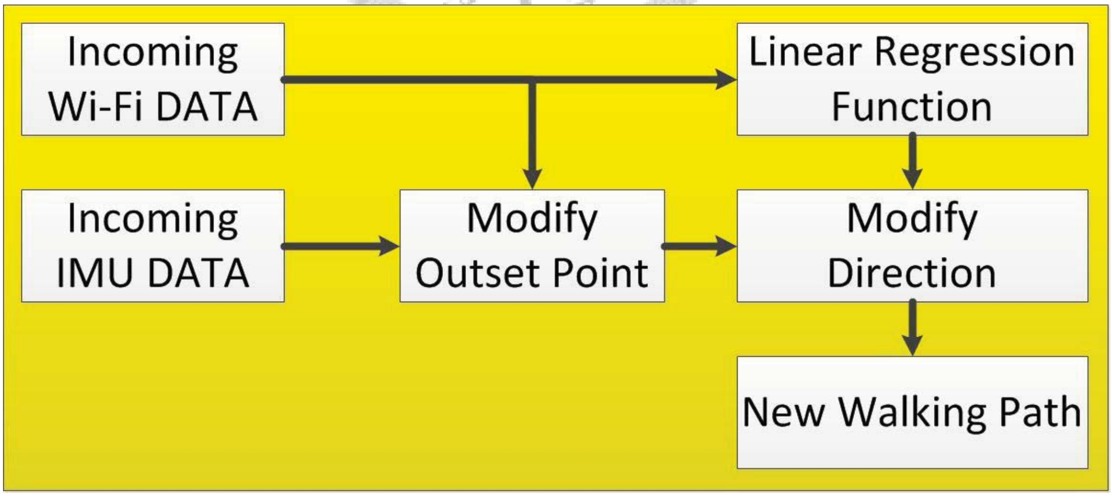


Figure 3.2: MODA fusion structure

The detailed steps are as following.

First of all, based on the past statistical observations we have, we want to find the start point. The object function is showed below.

$$\arg\min_{i,j} f\left(i,j\right) := \left\{i,j \mid \forall x,y : f\left(x,y\right) \geq f\left(i,j\right)\right\} \tag{4}$$

$$\text{Where } f\left(i,j\right) = \sum_k \begin{matrix} sqrt\left(\left(i - W[k].pixelx\right)^2 + \left(j - W[k].pixely\right)^2\right) \\ - abs(total\_distance - W[k].distance \end{matrix} \tag{5}$$

where k is the index of the $k\text{-}th$ Wi-Fi historical data, *W[k].pixelx* and *W[k].pixely* are the absolute coordinates of X-axis and Y-axis respectively at time k from our Wi-Fi positioning system, *W[k].distance* is the walking distance from the beginning to the time that the k-th Wi-Fi positioning result came out, *total_distance* is the total walking distance at that time, function $abs\left(\bullet\right)$ returns an absolute value of $\left(\bullet\right)$, function $sqrt\left(\bullet\right)$ returns a square root value of $\left(\bullet\right)$. We want to find out the desired position $\left(i,j\right)$ which has the smallest value in equation (4).

Secondly, we use the whole history of Wi-Fi positioning results to calculate a linear regression function as the possible heading.

Let linear regression function be

$$f\left(W\right) = aW + b \tag{6}$$

where W is a vector that stored the history of Wi-Fi positioning results.

Then the coefficients a, b are calculated by the following equations.

$$E = \sum \left(f\left(W_{x_i}\right) - W_{y_i} \right)^2 = \sum \left(aW_{x_i} + b - W_{y_i} \right)^2 \tag{7}$$

$$\begin{aligned} \frac{\partial E}{\partial a} &= 0 \rightarrow a\sum W_{x_i}^2 + b\sum W_{x_i} - \sum W_{x_i} W_{y_i} = 0 \\ \frac{\partial E}{\partial b} &= 0 \rightarrow a\sum W_{x_i} + nb - \sum W_{y_i} = 0 \end{aligned} \tag{8}$$

$$\begin{aligned} a &= \frac{\left(\sum W_{x_i}\right)\left(\sum W_{y_i}\right) - n\left(\sum W_{x_i} W_{y_i}\right)}{\left(\sum W_{x_i}\right)^2 - n\left(\sum W_{x_i}^2\right)} \\ b &= \frac{\left(\sum W_{x_i} W_{y_i}\right)\left(\sum W_{x_i}\right) - \left(\sum W_{y_i}\right)\left(\sum W_{x_i}^2\right)}{\left(\sum W_{x_i}\right)^2 - n\left(\sum W_{x_i}^2\right)} \end{aligned} \tag{9}$$

Thirdly, we defined a Fitting Function (Figure 3.3) to estimate the initial heading. Where IMU[i].x and IMU[i].y are the recorded data from IMU at moment t with the x-axis value and y-axis value respectively, d is the possible direction of the estimated IMU path, $\cos(\bullet)$ is the cosine function which returns the cosine value of $(\bullet)$, $\sin(\bullet)$ is the sine function which returns the sine value of $(\bullet)$, $\text{fabs}(\bullet)$ returns the float absolute value of $(\bullet)$, $\text{sqrt}(\bullet)$ returns the square root value of $(\bullet)$ and sum is the accumulated distance from each point in IMU to the calculated linear regression function.

Finally, the current position is calculated by function (10) and (11).The x, y, d values are determined by fitting function and m is the last index of vector IMU.

$$X = \left(IMU[m].x \bullet \cos\left(d \bullet PI/180\right) - IMU[m].y \bullet \sin\left(d \bullet PI/180\right) \right) + x \tag{10}$$

$$Y = \left(IMU[m].x \bullet \sin\left(d \bullet PI/180\right) + IMU[m].y \bullet \cos\left(d \bullet PI/180\right) \right) + y \tag{11}$$

Fitting Function : $f(x, y, d)$

```
sum = 0.0

For each node i in IMU vector

do

    tempx = (IMU[i].x*cos(d*PI/180) - IMU[i].y*sin(d*PI/180)) + x;

    tempy = (IMU[i].x*sin(d*PI/180) + IMU[i].y*cos(d*PI/180)) + y;

    sum += fabs(a*tempx-tempy+b*sqrt(a*a+1);

return sum
```

Figure 3.3: Fitting function

3.4 MODA Particle Filter (MPF)

The key idea of particle filtering is to represent the posterior density $p(X_t \mid Z_t)$ by a set of random samples (particles) with corresponding weights and make estimations upon these samples and weights. When the number of samples is enormous, this kind of particle filter closes to the optimal Bayesian estimate. Now we deem tracking the walking man as a dynamic system, of which the evolution is defined by the following state space model:

$$
\begin{aligned}
X_t &= f\left(X_{t-1}, I_{t-1}\right) \\
Z_t &= h\left(X_t\right) + Mn_t
\end{aligned}
\tag{12}
$$

With the following elements

$f(\bullet)$: state transition function
$h(\bullet)$: measurement function

$X_t = \{\chi_{0,}\chi_1,...,\chi_t\}$ state vector

I_{t-1} movement input

$Z_t = \{z_1, z_2,..., z_t\}$ measurement vector

Mn_t measurement noise

The state $\chi_t = (x_t, y_t, \theta_t)$ stands for the location (x_t, y_t) and start direction (θ_t) at moment t. The dynamic process is expressed in discrete regarding the motion model, thus when new measurement is available, an approximation is made. The measurement $z_t = (I_t^x, I_t^y, W_t^x, W_t^y)$ contains the moving vector $I_t = (I_t^x, I_t^y)$ from last position to time t and Wi-Fi positioning result $W_t = (W_t^x, W_t^y)$ which is a predefined calibration point outputted from KNN at moment t. The measurement noise Mn_t is assumed Gaussian. We find the most possible position that the user currently stand by estimating X_t by the set of all measurements Z_t. The particle filter directly estimates this posterior density of the state by the following equation [38]

$$p(\chi_t \mid Z_t) \approx \sum_{i=1}^{N_p} weight_t^i \delta(\chi_t - \chi_t^i) \tag{13}$$

Where χ_t^i is the i-th particle of the posterior, $weight_t^i$ is the weight of the particle and $\delta\left(\chi_t - \chi_t^i\right)$ function is the Dirac delta measure [15]. Then, we could transform the intractable continuous-time dynamic system into tractable discrete sums of weighted particles [39].

The flow chart of MPF is showed in Figure 3.4, as you can see, we have 7 stages, initialization stage, measurement update stage, propagation stage, map filtering stage, resampling stage, normalization stage, and estimation stage. The function and detailed procedures of each stage are discussed below.

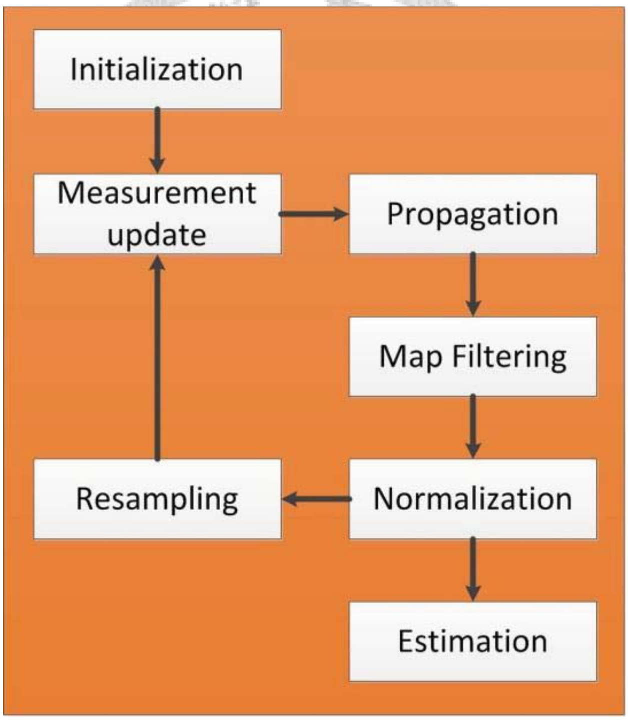


Figure 3.4: The flow chart of MODA Particle Filter

3.4.1 Initialization Stage

At this stage, we have to give all particles initial conditions. The steps are as following.

Step 1. Choose an outset point by Wi-Fi positioning system.

Step 2. Scatter N_p particles from normal distribution $N\left(\mu_W, \sigma_W\right)$, where N_p is the number of particles, μ_W and σ_W are the predefined mean and standard deviation from experiments in Wi-Fi positioning system.

Step 3. Set particles' startup orientation from uniform distribution $U\left(0,360\right)$

Step 4. Set all particles' weight $= 1/N_p$, where weight means the credibility of that particle.

3.4.2 Measurement Update Stage

When measurements are available at moment t, the prior is updated with observations $Z_t = \left(I_t^x, I_t^y, W_t^x, W_t^y\right)$ via Bayes' rule. However, before updating the prior, we use MODA to pre-process the observations Z_t. As described in chapter 3.3, after the calculation of MODA, the output is a position, just like what the Wi-Fi positioning system do. The difference is that we use the information from both IMUs and Wi-Fi to predict a position rather than utilizing the result from Wi-Fi positioning system directly. According to the measurements z_t and output from MODA $M_t = \left(m_t^x, m_t^y\right)$, we calculate $p\left(\overline{z_t} \mid \chi_t^i\right)$ with a new measurement $\overline{z_t} = \left(I_t^x, I_t^y, m_t^x, m_t^y\right)$.

Where $\left(m_t^x, m_t^y\right)$ is a position estimated by MODA, m_t^x is the value of X-axis, m_t^y is the value of Y-axis and $p\left(\overline{z_t} \mid \chi_t^i\right)$ is the likelihood function that describe the estimated walking vector is Normal distributed with the measurement $\left(I_t^x, I_t^y\right)$ and assumes that the position estimated by MODA is normal distributed around the true position. The likelihood function $p\left(\overline{z_t} \mid \chi_t^i\right)$ is defined as following:

$$p\left(\overline{z_t} \mid \chi_t^i\right) = \frac{1}{\sqrt{2\pi\sigma^2}} e^{-\frac{\left(M_t - \chi_t^i\right)}{2\sigma^2}} \tag{14}$$

3.4.3 Propagation Stage

The propagation step generated the state χ_t of a new particle by drawing from the state transition model $\chi_t = f\left(\chi_{t-1}, I_{t-1}\right)$

First, the moving vector is disturbed according to an uncertain model, because of the perturbing measurement noise from IMU device. We assume that both the changing heading and walking length are disturbed by Normal random variables, draw S_t^x from $N\left(\mu_t^{ix}, \sigma_t^{ix}\right)$, S_t^y from $N\left(\mu_t^{iy}, \sigma_t^{iy}\right)$ and S_t^θ from $N\left(\mu_t^{i\theta}, \sigma_t^{i\theta}\right)$, where $\left(\mu_t^{ix}, \sigma_t^{ix}\right)$ are the measurement I_t^x and the standard deviation of I_t^x respectively, $\left(\mu_t^{iy}, \sigma_t^{iy}\right)$ are the measurement I_t^y and the standard deviation of I_t^y respectively, $\left(\mu_t^{i\theta}, \sigma_t^{i\theta}\right)$ are zero and the standard deviation of changing heading error. Those three standard deviations $\left(\sigma_t^{ix}, \sigma_t^{iy}, \sigma_t^{i\theta}\right)$ are set by experiments, and they are set to 10% error, 10%

error and 5% error respectively.

Thereafter, we have three new values, $\left(S_t^x, S_t^y, S_t^\theta\right)$, which are disturbed by Gaussian random variables.

$$
\begin{aligned}
S_t^x &\sim N\left(\mu_t^{ix}, \sigma_t^{ix}\right) \\
S_t^y &\sim N\left(\mu_t^{iy}, \sigma_t^{iy}\right) \\
S_t^\theta &\sim N\left(\mu_t^{i\theta}, \sigma_t^{i\theta}\right)
\end{aligned}
\tag{15}
$$

Then these values are used to predict the next state as following:

$$
\chi_t^i = \begin{cases} \theta_t^i = \theta_{t-1}^i + S_t^\theta \\ x_t^i = x_{t-1}^i + S_t^x \bullet Cos\left(\theta_t^i\right) - S_t^y \bullet Sin\left(\theta_t^i\right) \\ y_t^i = y_{t-1}^i + S_t^y \bullet Sin\left(\theta_t^i\right) + S_t^x \bullet Cos\left(\theta_t^i\right) \end{cases}
\tag{16}
$$

3.4.4 Map Filtering Stage

In some public buildings such as Nang Gang Exhibition Center or MRT stations in Taipei, the map information is available online. Therefore, we could use this additional useful information to reduce the uncertainty of the walking trajectory in such places. With particle filter, the approximation can be ameliorated by deleting unreasonable particles that have impossible trajectory. Accordingly, the weight of each particle should be re-evaluated by the equation (13)

$$
weight_t^i = \begin{cases} 0 & ,if\ \ the\ position\ is\ impossible \\ weight_{t-1}^i \bullet p\left(\overline{z_t} \mid \chi_t\right) & ,otherwise \end{cases}
\tag{17}
$$

3.4.5 Normalization Stage

At each iteration of the process, the weights of particles can alter rapidly and because this system is a non-Gaussian dynamic system, the sum of the weights of particles might not equal to one. Hence, in order to keep the sum weights equaling one, we use the following equation (14) to normalize the weights of particles.

$$\overline{weight_t^i} = \frac{weight_t^i}{\sum_{i=1}^{N_p} weight_t^i} \quad (18)$$

3.4.6 Estimation Stage

The possible location of the user is estimated by the particle with maximal weight, noted as $\max_{\chi_t}$ and the equation is below.

$$\arg\max_i f(i) := \{i \mid \forall z : f(z) \le f(i)\} \quad (19)$$

$$\text{Where } f(i) = weight_t^i \quad (20)$$

$$\max_{\chi_t} = \chi_i \quad (21)$$

3.4.7 Resampling Stage

A degeneracy phenomenon occurs when after walking a few steps, some particles will have negligible weights. It has been shown[40] that the variance of the importance weights is only enlarging over time, so it is impossible to avoid such phenomenon. For this reason, we use the resampling algorithm[41] to eliminate such problem. However, though the resampling algorithm diminishes the effects of the degeneracy problem, it brings another well-known problem, sample impoverishment. It is especially severe in the situation of small process noise. As a matter of fact, in such circumstance, all particles will collapse to a single point within a few steps. Because the diversity of the paths of all particles is decreased, the approximation based on these particles degrades. Consequently, we can't do the resampling on every step. There are many approaches proposed to solve this problem [42-45].

Chapter 4

Experiments

In this chapter, we introduce the environment, devices we use and the parameters in our experiments. Our algorithm is compared with another Wi-Fi and IMU fusion algorithm with its Wi-Fi likelihood function [2] (we call it WPF for the abbreviation of Wi-Fi Particle Filter), NN(Nearest Neighbor) which is the core algorithm of RADAR [18] and particle filter approach used in [16] when the information of start point and orientation is not available. Noted that, we only consider the nearest neighbor instead of k neighbors in Wi-Fi positioning system, KNN becomes NN. Furthermore, we just take out the assumptions of knowing the outset point and direction in WPF. Accordingly, WPF remains its functionality.

4.1 Experiment Environment

Our experiments were conducted in the corridor of fourth floor of Taipei NanGang Exhibition Center which is approximately a $7200m^2$ indoor building, the floor plan could be downloaded on-line [46], or you can see the Figure 4.1, which is the original map from the internet. We defined 156 reference points on the floor plan and marked them on the floor of the building as red points which were site-surveyed approximately every 3 meters with signal strength readings being taken 100 samples in offline phase whereas we take 10 samples in online phase. There are totally 24 access points in this building without knowing its position. The standard deviation and the mean error of Wi-Fi positioning system are chosen by experiments, the IMU step error rate and IMU heading error rate are defined by experiments as well. These parameters are listed in Table 4.1and Table 4.2. The example of device setup is showed in Figure 4.2.

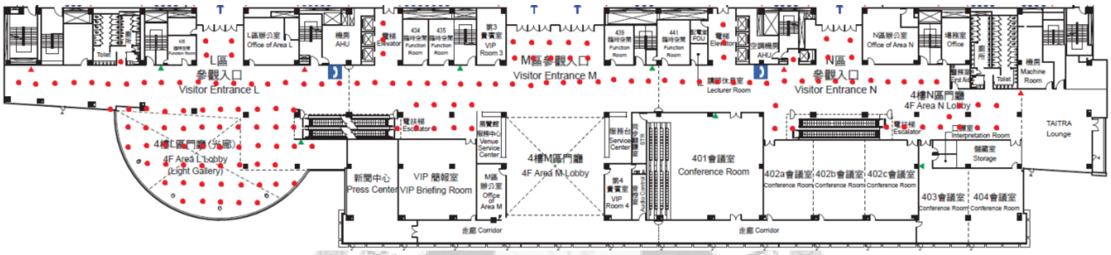


Figure 4.1: Radio Map of the corridor of fourth floor of Taipei NanGang Exhibition Center. The red dots are predefined calibration points.

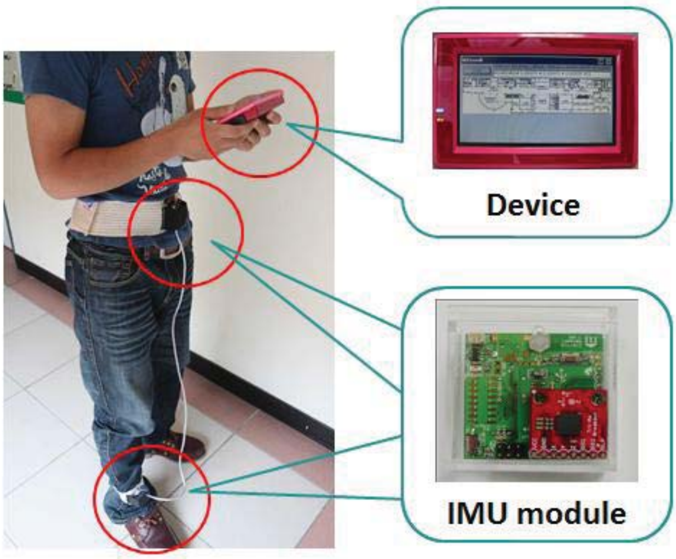


Figure 4.2: Example of device setup

Table 4.1: Experiment Devices

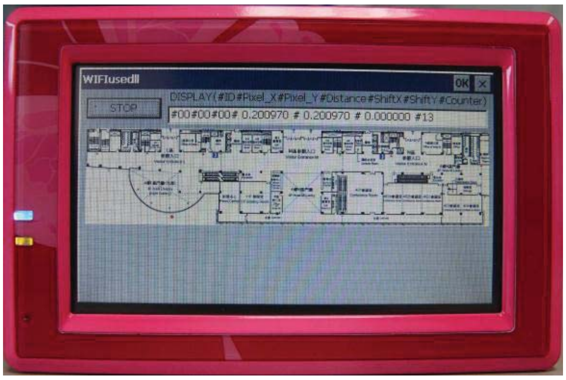
Hand-held Navigation Device  Operating System : Win CE 6.0 Processor : Samsung S3C6410 533MHZ RAM : 128MB Storage : 2GB Wi-Fi : Marvell 88W8686
Server Operating System : Windows 7 Processor : Intel Core Duo CPU T2400 1.83GHz RAM : 2039MB Storage : 160GB Network : HSDPA 4Mbps / HSUPA 1 Mbps

Table 4.2: Experiment Parameters

Wi-Fi access points : 24
Number of reference points : 156
Distance between reference points : 3-meter
Wi-Fi scanning period : 1 second
Wi-Fi offline sample size : 100
Wi-Fi online sample size : 10
Height of Hand-held Device : 1.2 m
Standard deviation of Wi-Fi σ_W : 4.843958
Mean value of Wi-Fi μ_W : 8.410209
Number of Particles : 13000
K-Nearest Neighbor - K : 1

4.2 Experiment Paths

To verify our MODA Particle Filter (MPF), we set up three different ground truth paths, which are straight line walk, converse-U shape walk and N shape walk. And for simplicity, we use the term path 1, path 2 and path 3 to substitute the terms used in original ones respectively. As a matter of fact, these paths represent different situations, path 1 is long and simple, path 2 has two turning points and path 3 is short and having two turning points. Through these paths we could evaluate the efficiency of our approach in time and space. In other words, we expect that our approach could find out the interested position faster than others and we are looking forward to seeing that our approach outperforms others when the walking distance is long. In order to make our analysis simple in these paths, we all started from a reference point and also stopped at another reference point. Furthermore, we use timestamps to record the moment that we receive the IMU and Wi-Fi data from IMU devices and Wi-Fi positioning server respectively, which are used to rebuild the real walking path that will then be utilized to evaluate the efficiency of these algorithms.

4.2.1 Path 1 – a straight line walk

As you can see in Figure 4.3, in this walk, we start from the “4F Area N Lobby” and walk along the corridor to the “Visitor Entrance L”. This walk evaluates someone comes to here by stairs, and his destination is “Visitor Entrance L”.

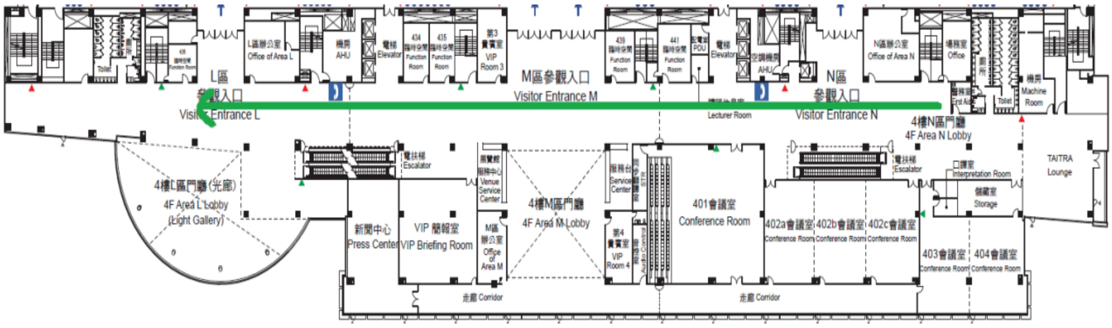


Figure 4.3: Path 1 – a straight line walk

4.2.2 Path 2 – a converse – U shape walk

The route planning is showed in Figure 4.4, in this walk, we expect the user comes up by the electricity staircase with a handrail and he comes here from a meeting in "Conference Room 402a". Therefore, he walks toward the main corridor then takes a right turn when reaching the main corridor. After that, he walks along the corridor until he sees the "Conference Room 402a" he takes a right turn again. Lastly, he walks into the "Conference Room 402a" to have a meeting.

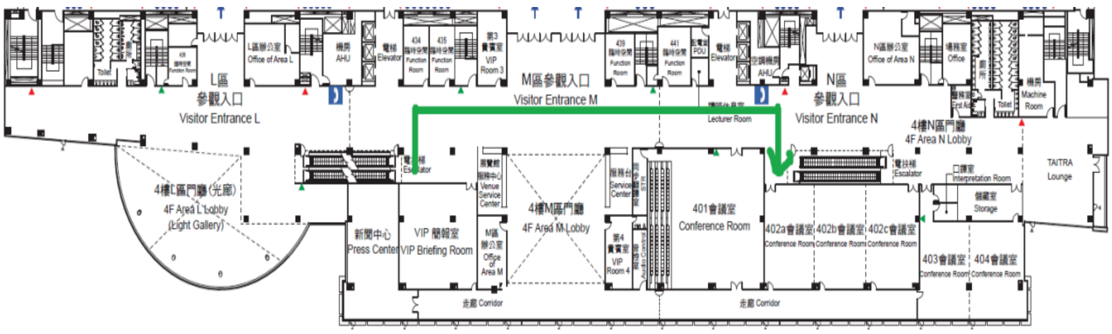


Figure 4.4: Path 2 – a converse-U shape walk

4.2.3 Path 3 – an N shape walk

As you can see in Figure 4.5, in this walk, we assume that a user just finished the meeting, so the start point is right next to the door of “Conference Room 402a”. Owing to the tiring meeting, the user is likely exhausted. Therefore that he takes a small walk to the nearest elevator.

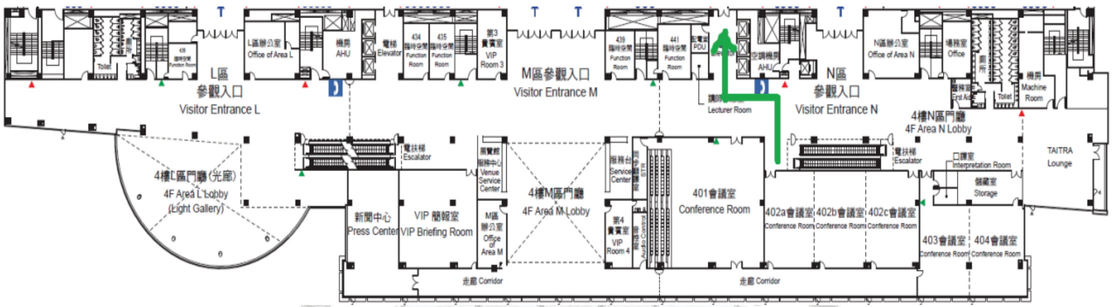


Figure 4.5: Path 3 – an N shape walk

4.3 Experiment Results

In the following sections we discuss the performance of MPF, WPF, NN and PF in three distinct paths. We will show estimated paths from different approaches and the cumulative percentage of error distance as well to prove the efficiency of our approach.

4.3.1 Path 1 – a straight line walk

In path 1, the walking style is a straight line walk, the walking distance is 121.9 meters and the duration of walking period is 133 seconds. The red line represents the ground truth, blue line is the path that estimated by Wi-Fi Particle Filter (WPF), the green line stands for the walking path approximated by MODA Particle Filter (MPF), the purple line is the NN (Nearest Neighbor) and the black line is PF (Particle Filter). We can see that in the beginning of this walk (Figure 4.7), MPF and WPF have terrible trajectories. The reason is that there were too few clues to determine the current position of the walk person. When this person walks a period of time, the green line and blue line started to converge to the ground truth. In other words, the more information we have the higher probability that we could get an accurate localization. Here the information means the Wi-Fi positioning results and the recorded path by IMU. WPF seems having good performance in the trajectory picture, but actually its position jumped back and forth under the overlapped lines. This phenomenon could be observed in Figure 4.6 which is the picture of the cumulative distribution function of MPF, WPF, NN and PF respectively. As a result of depending on Wi-Fi too much, WPF is as easily drifted away as Wi-Fi. On the other hand, MPF relies on the whole history of Wi-Fi points and the total walking path rather than one single Wi-Fi point thus reducing the probability of strayed away by specific one severely inaccurate Wi-Fi point. It can be seen in Table 4.3

that MPF has smallest mean error (3.12) whereas the mean error of WPF is 6.43m. In such case, WPF, MPF an PF couldn't take much advantage of map information since that the walking style is too simple to filter out shift error, which resulted in the particles that are scattered along the corridor. Therefore, the standard deviation of both MPF and WPF is quite high compared to other walking paths. However, MPF outdid WPF with the enhancement up to 206% in mean error in this case. Nevertheless, the standard deviation of MPF is the lowest which shows that MPF is more stable than WPF, NN and PF.

Table 4.3: Positioning error and stand deviation in path 1

	MPF	WPF	NN	PF
Mean error (m)	3.12	6.43	8.66	8.05
Standard deviation (m)	3.38	5.60	4.32	4.23

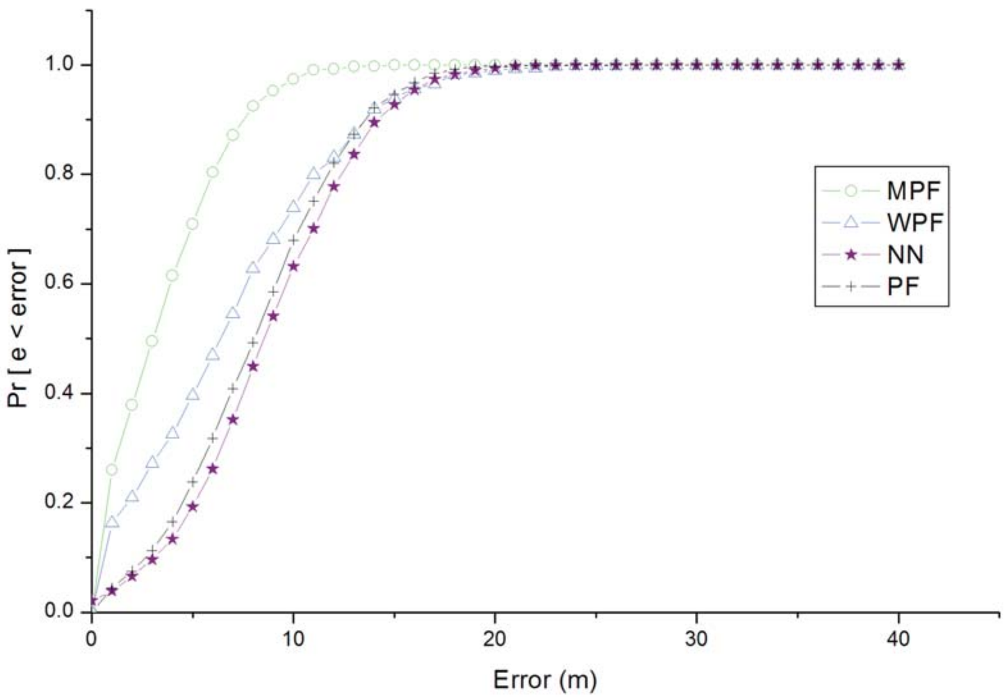


Figure 4.6: Position error CDFs in path 1

Figure 4.7: Estimated trajectories in path 1

4.3.2 Path 2 – a converse-U shape walk

In path 2, the walking style is a converse-U shape walk, the walking distance is 74.6 meters and the duration of walking period is 96 seconds. The five colored lines represent for the same relationship as declared above. Though both the trajectories of MPF and WPF look like random walks at the start, MPF found the right way faster than WPF which could be seen in Figure 4.8 and Figure 4.9. Owing to some diverged Wi-Fi points, the blue line was strayed from the real path in the middle of the walk. However, this path is long enough for convergence and there are two turning points that would help decreasing the ambiguities of locations in the map, so both mean error and standard deviation of MPF, WPF and PF are lower than path 1. Furthermore, we could see the curves in Figure 4.8, the green curve and blue curve is close in the beginning which means they could achieve position errors below one meter during the journey. Despite that they are close to each other, the green line ascends rapidly whereas the blue line rises slower. The reason is that MPF finds the real path faster than WPF. The black line PF in path 2 performs poorer than path 1. It is because that the start region of path 2 is bigger than that of path 1 which results in slower convergence to real path. Under such circumstance, MPF prevails WPF with the increment up to 203% in mean error (Table 4.4).

Table 4.4: Positioning error and stand deviation in path 2

	MPF	WPF	NN	PF
Mean error (m)	2.95	6.01	8.40	8.64
Standard deviation (m)	2.38	5.61	4.27	3.74

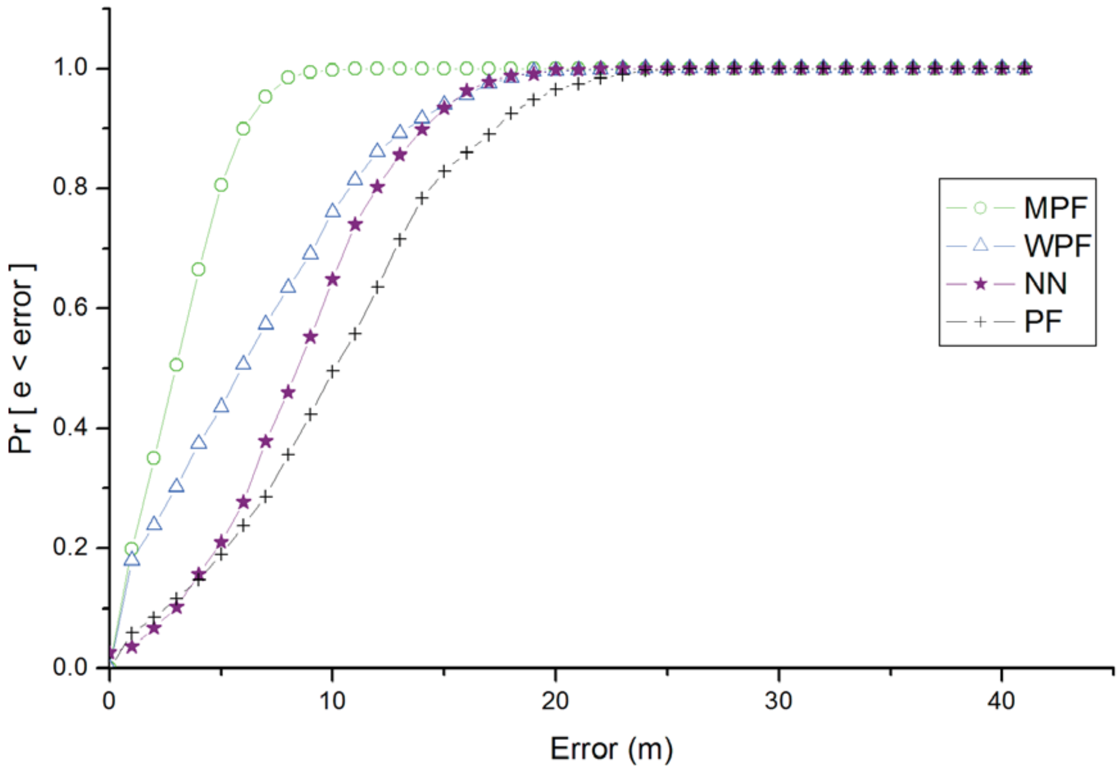


Figure 4.8: Position error CDFs in path 2

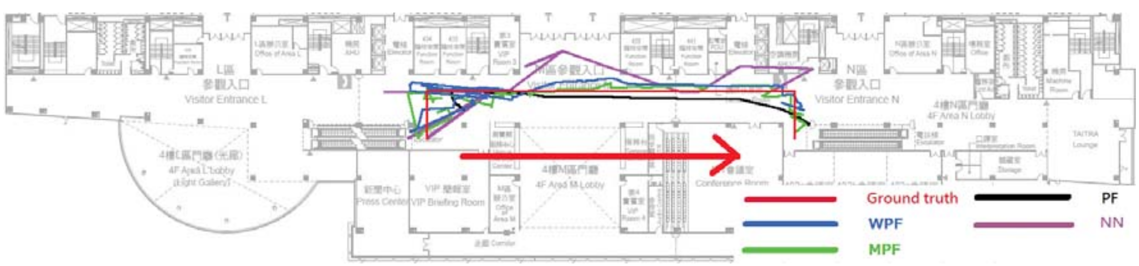


Figure 4.9: Estimated trajectories in path 2

4.3.3 Path 3 – an N shape walk

In path 3, the walking style is an N shape walk, the walking distance is 25.6 meters and the duration of walking period is 32 seconds. The five lines colored with blue, green, purple, black and red stand for the same relationship as mentioned before. From the Figure 4.11, we could also see the influence of uncertainties in direction and outset point in the beginning. Just as in other cases, both MPF and WPF converge to the ground truth after the person walk a few steps. Figure 4.10 proposes a performance comparison among three positioning techniques by illustrating the cumulative distributions of MPF, WPF, NN and PF. As you can see the four curves of path 3 are closer than other paths, the main reason is that the walk is too short that the MPF just find its way to the ground truth, the walk finishes. Noted that PF has the poorest performance in this path, the explanation is that the corridor that is in front of the elevators is too narrow that few particles could walk inside to in. Owing to its method of finding the possible position which is calculated by averaging all the particles' positions, the estimated position has no chance being in that narrow corridor unless all particles are in there. Figure 4.10 shows that MPF excels WPF no matter in short range or long range error. The mean error of MPF is better than WPF with the augmentation up to 159% (see Table 4.5).

Table 4.5: Positioning error and stand deviation in path 3

	MPF	WPF	NN	PF
Mean error (m)	3.30	5.25	7.06	9.92
Standard deviation (m)	2.07	3.51	2.78	5.58

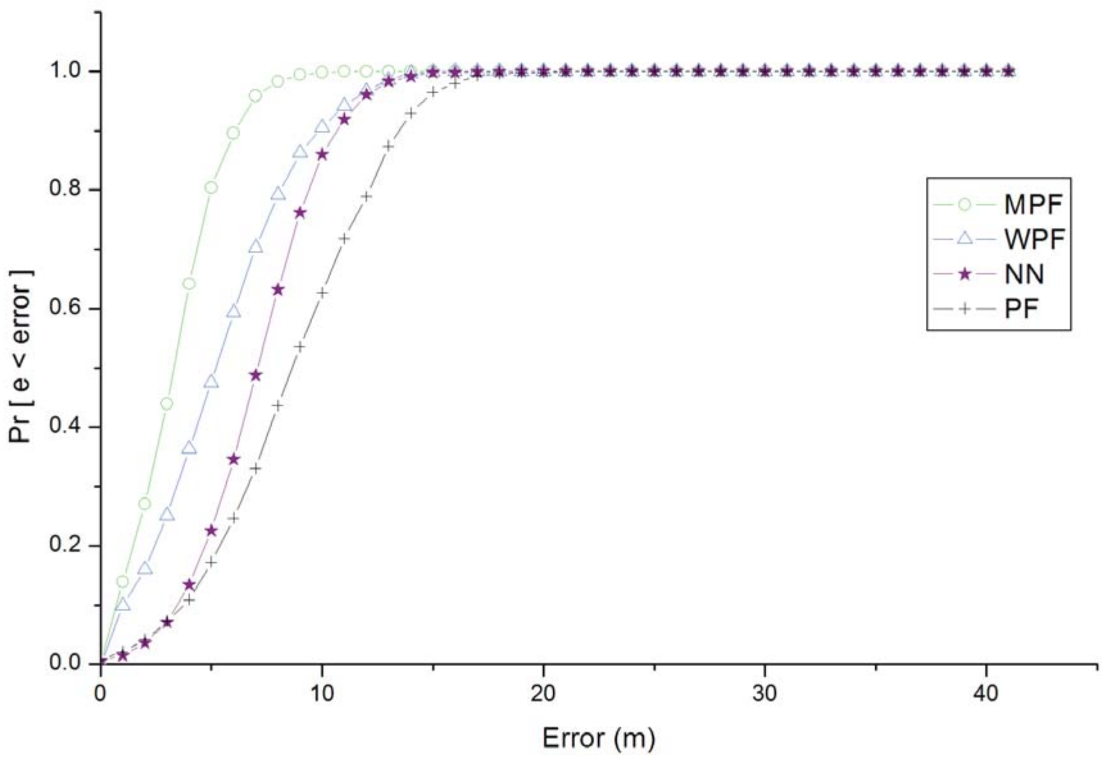


Figure 4.10: Position error CDFs in path 3

Figure 4.11: Estimated trajectories in path 3

As we expected, the Wi-Fi positioning system with NN and Particle Filter (PF) shows poor performance relative to MODA Particle Filter (MPF) and Wi-Fi Particle Filter (WPF). The reason is that it is memory-less which means that NN doesn't take the history into account, consequently cannot filter out any noise in the estimates. Moreover, in such a huge building, $7200m^2$, the Wi-Fi positioning system – RADAR(NN) could not achieve good performance because most of the signals from access points are not blocked by walls, rooms or furniture. PF uniformly scatters the initial particles in a region which is determined by Wi-Fi positioning system. Because the width of the corridor is approximately 7.35 meters, those particles are hard to converge into a small cluster by only using the map constraints. The results of these three paths indicate that our algorithm outperforms other algorithms by achieving smaller average error distance and smaller standard deviation which means that our algorithm is more stable and accurate.

Chapter 5

Conclusion

In this thesis, we present a positioning system that fuses a Wi-Fi positioning system with IMU. Wi-Fi positioning system is implemented with NN in RADAR while we use IMU to estimate the length of each step and the turning angle. As the initial information is not available, we first set the start point of particles by Wi-Fi with Gaussian distribution and the direction is uniformly distributed between 0 and 360. Then we use the whole history of Wi-Fi points and the path that was recorded by IMU to modify the outset point and the initial direction at each iteration. Extensive experiments were carried out showing that our approach yields drastic improvements over previously introduced approaches that use particle filters with the fusion of Wi-Fi points and IMU. In our experiments, MPF outdid WPF with the enhancement up to 206% in path 1, prevails WPF with the increment up to 203% in mean error in path 2 and the mean error of MPF is better than WPF with the augmentation up to 159% in path 3. All the results indicate that our approach is more applicable than introduced solutions when initial knowledge is not given.

In our tracking system the user do not need to know any information about the building. Such system could potentially be utilized to enable location-aware applications in large buildings, where the setup of high accuracy positioning system is either expensive or impractical. Navigation in museums or exhibition halls, tracking a missing children and guidance for the blind are some examples of location based services. Since MPF could achieve the rate of accuracy less than 4-meters in large building, location based services can benefit from our system.

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