A Hybrid Algorithm Based on WiFi for Robust and Effective Indoor Positioning

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Abstract*—Indoor positioning based on the Wireless Fidelity (WiFi) protocol and the Pedestrian Dead Reckoning (PDR) approach is widely exploited because of the existing WiFi infrastructure in buildings and the advancement of built-in smartphone sensors. In this work, a hybrid algorithm that combines WiFi fingerprinting and PDR to both exploit their advantages as well as limiting the impact of their disadvantages is proposed. Specifically, to build a probability map from noisy Received Signal Strength (RSS), a Gaussian Process (GP) regression is deployed to estimate and construct the RSS fingerprints with incomplete data. Mean and variance of generated points are used to estimate WiFi fingerprinting position by K-nearest weights from the probability of visible RSS measurements of the online phase. In addition, a particle filter is applied to fuse PDR and WiFi fingerprinting by using the information from RSS, inertial sensors and features of indoor maps. To demonstrate the potential of the proposed framework, two case studies are considered. In the first case, a comparison is made between GP regression with K-Nearest Neighbours (KNN) method to show the improvement with a sparse input data set. In the second case, the proposed framework is compared to both the fingerprinting approach as well as the PDR algorithm. The results show significant improvements from our proposed framework. The average positioning accuracy of our proposed system can be lower than 1.2 m, which was reduced by 48% and 70% compared with the WiFi fingerprinting and the PDR method, respectively.

***Index Terms*—Gaussian Process Regression, Particle Filter, WiFi, Pedestrian Dead Reckoning, Indoor Positioning**

I. INTRODUCTION

The widespread deployment of wireless technologies is enabling numerous applications using indoor positioning, such as health care monitoring, guided navigation in museums, universities, malls, airports, and general industrial environments. Since the Global Positioning System (GPS) cannot guarantee location service because a line-of-sight transmission between receivers and satellites is not possible in an indoor environment, many approaches in current positioning technologies have been proposed such as Ultra Wide Band (UWB) [1], Radio Frequency Identification tags (RFID) [2], Bluetooth Low Energy (BLE) [3], WiFi [4], [5], Pedestrian Dead Reckoning (PDR) using inertial sensors [6]. Among them, WiFi technology based on the Received Signal Strength (RSS) has become a common solution for indoor positioning because of the convenience of measuring this value directly from smart-phones and other mobile devices.

In order to estimate position from RSS, path-loss model-based or fingerprinting based approaches can be used. Firstly, a "path-loss" based approach is a technique that converts the values of RSS from the access points to the mobile receiver into distances based on a signal propagation model [7]. However, the position relationship is highly complex due to multi-path, metal reflection and interference noise [8]. Thus, the path-loss model may not be adequately captured by an invariant model. Secondly, fingerprinting/sense analysis is a technique that estimates the position based on a scene analysis. This technique estimates the user's position relied on the similarities between the RSS measurements of online phase and RSS of the offline phase training [5], [9]. The main advantages of WiFi fingerprinting are that it takes advantage of current WiFi infrastructures and the location of the access points can be unknown. On the other hand, the disadvantages of the fingerprinting method include the need for dense training coverage and the poor extrapolation of areas not covered during the training phase. During the offline phase, it can be extremely time-consuming and labour-intensive to build substantially large fingerprinting databases [9].

Another widely adopted localization approach is PDR [10], [6], which leverages inertial sensors to estimate the displacement of pedestrians relatively to their previous position. The main challenge in this approach is that the inertial sensors in commercial smart-phones often suffer from imperfect calibration and noisy measurements [9]. In addition, step counting is currently a major method to capture the walking path and the movement of pedestrians [10]. The estimated location of PDR is often drifted when travelling a long distance due to inaccurate measurement of step detection, step length and heading. The drift of PDR can be corrected to achieve high accuracy by combining with WiFi fingerprinting using Kalman filter [11] or Particle filter [12], [13], [14]. Even though extensive work has been done in this area, some important issues still need to be explored and resolved to improve effectiveness and accuracy.

In this article, an indoor positioning system is presented. In addition to WiFi RSS, it also utilises inertial sensors in smart-phones and available maps of buildings. In particular, a novel hybrid framework is proposed based on the combination of the WiFi fingerprinting and PDR approaches, as shown in Fig. 1. The proposed framework aims at achieving location robustness and accuracy by combining a number of techniques:

- *Constructing a "WiFi map"*. With the aim of reducing the time needed for data training during the offline phase

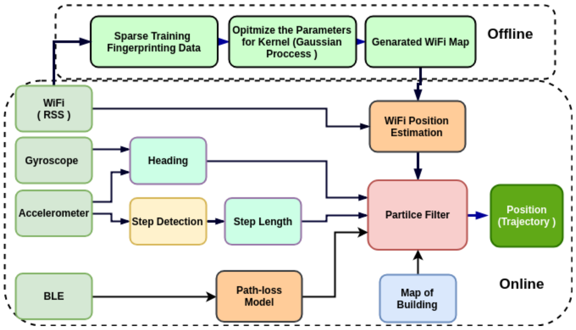


Fig. 1: The proposed hybrid WiFi indoor positioning system.

and for improving the accuracy of WiFi fingerprinting, a Gaussian process (GP) regression is deployed. This makes it possible to obtain the mean and variance of the considered WiFi map based on the correlation between RSS of sparse training points.

- *Motion estimation of PDR*. To detect motion and calculate the movement of pedestrians using smart-phones, we aim at improving the step detection and stride length algorithm by using only the accelerometer. Besides, instead of using the absolute heading from the compass, we apply Magdwick filters [15] by combining values from the accelerometer and the gyroscope to avoid the effect of magnetic fields on the magnetometer and to estimate the relative heading.
- *Location hybrid method*. An efficient method is proposed to evaluate the user's position by real-time RSS measurement and the WiFi map. Then, a hybrid method is applied by using a particle filter for combining the WiFi estimation with the PDR and the features of the building map. This hybrid makes the indoor positioning system able to achieve high accuracy and robustness.

The rest of the paper is organised as follows. The WiFi fingerprinting, PDR and hybrid method are described in Section II. The experimental setup and the discussion of the experimental results are outlined in Section III. Finally, conclusions and future works are discussed in Section IV.

II. METHODOLOGY

In this section, the WiFi fingerprinting based on the GP regression to build a WiFi map is presented. Furthermore, improvements of different methods for PDR are described. Finally, the proposed hybrid algorithm for indoor positioning is introduced.

A. Building WiFi fingerprinting maps by using a Gaussian process regression

Fingerprinting techniques require high-density training data to achieve high accuracy. However, the data collection is labour intensive. In this proposed framework, a GP regression is used to minimise the training time and to improve the effectiveness of WiFi fingerprinting [5]. GP has many advantages that makes it applicable for indoor positioning systems using WiFi RSS [4], [5]. It is non-parametric, continuous and correctly handles uncertainty in both process and estimation [16]. GP is especially useful because of the noisy RSS WiFi measurements due to various phenomena such as reflection, scattering and diffraction.

To generate a WiFi map using GP regression for the indoor positioning system from the training data, the GP relies on a covariance function kernel that establishes the correlation of values at different points. Assuming that $\mathbf{r} = \{r_i, i = 1, ..n\}$ is the observed RSS vector that includes n received access points (AP) at corresponding coordinate points in d dimension $\mathbf{x} = \{\mathbf{x}_i, i = 1, ..n\}$, $\mathbf{x}_i \in R^d$, so that the pair $(\mathbf{x_i}, r_i)$ represents the training data. Each observation r_i can be related to a transformation $f(x_i)$ through a Gaussian noise model from a noisy process as: $r_i = f(\mathbf{x}_i) + \epsilon$, where $\{\epsilon\}$ is the generated measurement noise from a Gaussian distribution with zero mean and variance σ_i^2. Any two output values, r_p and r_q are assumed to be correlated by a covariance function based on their input values $\mathbf{x}_p$ and $\mathbf{x}_q$:

$$cov(r_p, r_q) = k(\mathbf{x}_p, \mathbf{x}_q) + \sigma_n^2 \delta_{pq}, \tag{1}$$

where $k(\mathbf{x}_p, \mathbf{x}_q)$ is a kernel, σ_n^2 is the variance , δ_{pq} is 1 if $p = q$ and 0 otherwise. The kernel function considered in this work is squared exponential kernel as equation:

$$k(\mathbf{x}_p, \mathbf{x}_q) = \sigma_f^2 \exp\left(\frac{(\mathbf{x}_p - \mathbf{x}_q)^2}{2l^2}\right), \tag{2}$$

where σ_f^2 is the signal variance and l is the length scale that determines how strongly the correlation between points drops off.

From equation 1, the covariance over the corresponding observations $\mathbf{r}$ for all input values $\mathbf{x}$ becomes: $cov(\mathbf{r}) = \mathbf{K} + \sigma_n^2 \mathbf{I}$, where, $\mathbf{K}$ is the $n \times n$ covariance matrix of all pairs of training points. Then, training points are generated by the posterior distribution over function $\mathbf{x}_* = \{\mathbf{x}_i^*, i = 1, ..m\}$, given the training data set $\mathbf{x}, \mathbf{r}$ by:

$$p(\mathbf{r}_* | \mathbf{x}_*, \mathbf{x}, \mathbf{r}) \sim \mathcal{N}(\mu_{\mathbf{r}_*}, \sigma^2_{\mathbf{r}_*}), \tag{3}$$

$$\begin{aligned} \mu_{\mathbf{z}_*} &= \mathbf{k}_*^T (\mathbf{K} + \sigma_n^2 \mathbf{I}_n)^{-1} \mathbf{z}, \\ \sigma^2_{\mathbf{z}_*} &= k_{**} - \mathbf{k}_*^T (\mathbf{K} + \sigma_n^2 \mathbf{I}_n)^{-1} \mathbf{k}_*. \end{aligned} \tag{4}$$

where $\mathbf{k}_{**} = cov(\mathbf{x}_*, \mathbf{x}_*)$ is the vector variance of generated points $\mathbf{x}_*$ and $\mathbf{k}_* = cov(\mathbf{x}_*, \mathbf{x})$ is the vector of covariance between $\mathbf{x}_*$ and training points $\mathbf{x}$. In this work, The conjugate gradient descent method is utilised to optimise the hyper parameters of the function kernel. The WiFi map is built up by predicted points spaced $1m \times 1m$ apart.

B. Pedestrian Dead Reckoning

PDR is the technique that uses Inertial Measurement Units (IMU) to estimate the movement of a person by detecting steps, estimating stride lengths and the directions of motions. An IMU is integrated into most of the smart-phone and provides triaxial orthogonal accelerometers, gyroscopes, magnetometers, and even pressure sensors. PDR determines the next position using the previous position, step length and walking direction, which is expressed as follows:

$$\mathbf{x}_k = \mathbf{x}_{k-1} + L_k \begin{bmatrix} cos(\theta_k) \\ sin(\theta_k) \end{bmatrix}, \tag{5}$$

where $\mathbf{x}_t$ is the state vector of the device at time step k, L_k is the step length and θ_k is the walking direction at time step k. Some significant problems needs to be solved, such as estimation of step detection, step length, and walking direction.

1) Step Detection: Steps can be detected by measurements from accelerometers [11] or gyroscopes. In [12], an accelerometer is used by Normalised Auto-correlation based Step Counting. In this paper, we use an accelerometer based on the technique in [12], [10] with some slight modifications. The algorithm for step detection consists of the following steps:

- **Step 1**. Calculate the magnitude for the normalisation factor of every sample i:

$$a_i = \sqrt{a_{x_i}^2 + a_{y_i}^2 + a_{z_i}^2}. \tag{6}$$

- **Step 2**. Calculate the local acceleration deviation, to the foot activity and to remove gravity:

$$\sigma_{a_i} = \frac{1}{w}\sum_{j=i}^{i+w}(a_j - \bar{a_j}), \tag{7}$$

  where $\bar{a_j}$ is a local mean acceleration value, computed by this expression: $\bar{a_j} = \frac{1}{w}\sum_{q=i}^{i} a_q$, and w defines the size of the averaging window ($w = 50$ samples).
- **Step 3**. To discriminate between the state of walking and the state of standing, the deviation is gained by 10 times using the accumulated window ($w_g = 10$), according to the following equation: $\sigma_d = \sum_{j=i}^{i+w_g}(\sigma_{a_j})$, where σ_d is the deviation for the step detection.
- **Step 4**. Thresholding: a first threshold is applied to detect the step with high accelerations, the value can be calibrated by the user at $T(m/s^2)$. If $\sigma_{d_i} > T$ and previous value $\sigma_{d_{i-1}} < T$, the steps will increase by one.

Fig. 2 shows the magnitude of the accelerator deviation before and after using the accumulated window of this algorithm from an experiment. The threshold can be calibrated by the users through an Android application to fit with these smart-phone. In our experiments, we set a threshold equal to 4.

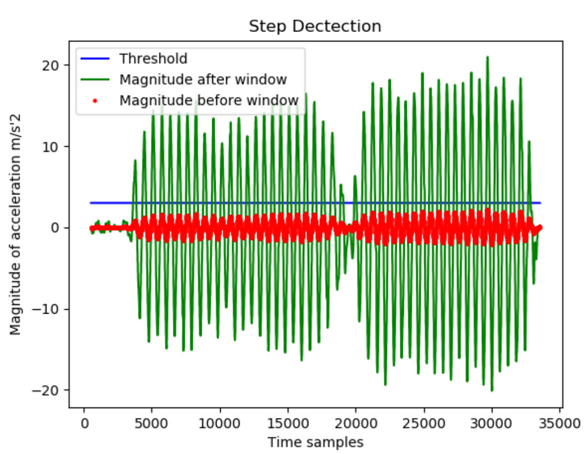


Fig. 2: The step detection from the accelerometer with the proposed algorithm.

2) Stride Length Estimation: Stride Length (SL) at every detected step is necessary to calculate the travelled distance by the person while walking. The SL can be approximated as a constant value [13]. however, it varies significantly depending on the person and according to different parameters, such as the length of the legs, walking speed and frequency. In this work, we use the algorithm proposed by Weinberg that achieve high accuracy by using an accelerometer with the PDR technique [10] for dynamic walking. The Weinberg algorithm is as follows:

- Compute the magnitude of accelerations, a_i, as in eq. 6
- Low-Pass filter this signal ($\widetilde{a}_i = LP(a)_i$). We use a filter of order 4 and cut-off frequency at 3 Hz.
- Estimate the SL using the Weiberg expression:

$$L = K\sqrt[4]{\widetilde{a}_{j_{max}} - \widetilde{a}_{j_{min}}}, \tag{8}$$

where $\widetilde{a}_{j_{max}}$ and $\widetilde{a}_{j_{min}}$ are the maximum and minimum acceleration values after the low-pass filter, respectively. K is the coefficient that needs to be selected experimentally or calibrated. This approach takes the dynamics of step length during walking into consideration.

3) Walking Direction Estimation: To track the user's path in PDR, the most crucial factor is the pedestrian walking direction. It can be estimated from orientation sensors, such as magnetometers and gyroscopes. The compass calculates the phone orientation relative to the perceived magnetic north [12]. However, the magnetometer will be affected by noise. Therefore, an accelerometer is also used as an alternative or in combination with the magnetometer to improve accuracy [10]. By fusing the output from these sensors, the heading can be accurately estimated by different algorithms, such as an Kalman filter [11], Complimentary filter, Madgwick filter, or Mahony filter [15]. It is important to have a reference for the heading direction for initialisation. Since it would be inconvenient for a user to start with a specific direction [11], we calculate the relative direction using an accelerometer and a gyroscope with a Madgwick filter [15]. It is not necessary to measure the absolute heading since an accurate heading-change estimation can be determined by using the particle filter. This is enough to guide the particles to propagate in the right direction.

C. Hybrid algorithm

As mentioned previously, only WiFi fingerprinting cannot achieve high accuracy in indoor environments. Moreover, the speed rate to get RSS measurements has significant latency. In our experiments, the RSS is approximately updated every two seconds. This means that the indoor positioning system using only WiFi can experience a low response in real-time navigation if pedestrians are moving fast. On the contrary, PDR can provide a high position accuracy in a short range, but it slowly drifts walking distance. In this work, a particle filter is utilised to combine PDR with WiFi fingerprinting as shown in Fig. 3. The particle filter is based on a set of randomly weighted samples (i.e., the particles) representing the density

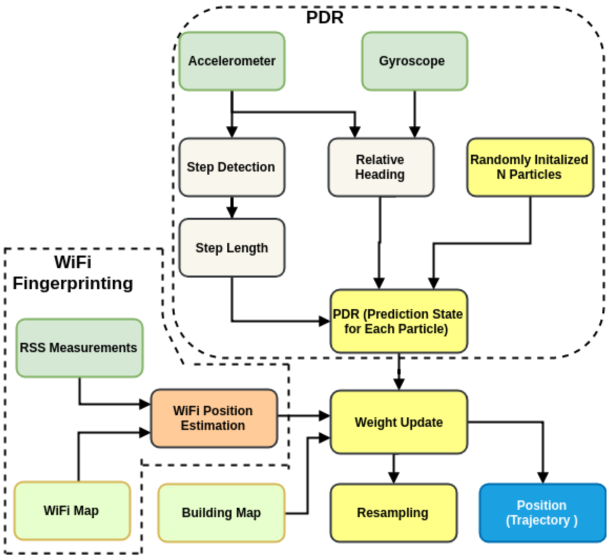


Fig. 3: The proposed hybrid framework for indoor positioning.

function of the user's position. Each particle explores the environment according to the motion model of the PDR. These weights are updated at each step once a new position from the WiFi fingerprinting is estimated. It is possible to constrain moverments like crossing the walls of a building map by forcing the weight at 0 for the particles having such a behaviour. In this work, the WiFi fingerprinting position is estimated by measuring the probabilities of new visible RSS in generated training points (WiFi map). We compute K-nearest weights of these probabilities. The steps of the algorithm are as follows:

- **Step 1**: for each access point l, the likelihood is computed as:
$$p(r_l|\mathbf{x}_*) = \frac{1}{\sqrt{2\pi\sigma^2_{\mathbf{x}_*}}} exp(-\frac{(r_j-\mu_{\mathbf{r}_*})^2}{2\sigma^2_{\mathbf{x}_*}}), \tag{9}$$
where $\mu_{\mathbf{z}_*}$ and $\sigma^2_{\mathbf{x}_*}$ are the means and the variances of predicted points $\mathbf{x}_*$ from equation 4.
- **Step 2**: giving the location $\mathbf{x}_*$, if each access point is considered independently, we can compute the weights of L visible access points in $m = [0, M]$ predicted training points by sum of logarithm probability from equation 9 as: $\psi_m = \sum_{l=1}^{L} \log(p(r_l|\mathbf{x}_*))$
- **Step 3**: Sort the weights, get K nearest weights ($\psi_k, k = [1, K], K \leq M$), then they are normalised by:
$$\bar{\psi}_k = \frac{\psi_k}{\sum_{k=1}^{K}\psi_k} \tag{10}$$
- **Step 4**: Estimate WiFi fingerprinting position $\hat{\mathbf{x}}_{wifi}$by
$$\hat{\mathbf{x}}_{wifi} = \sum_{m=1}^{K} \bar{\psi}_m \mathbf{x}_m, \tag{11}$$
where $\mathbf{x}_m$ is the K nearest predicted training points.

Assuming the state of i^th particle at step k as $\mathbf{x}^i_k = [x^i_k, y^i_k, \theta^i_k]$ has weight w^i_k. The Particle filter algorithm to combine WiFi fingerprinting and PDR is as follows:

- **Step 1. Initialisation** : set $k = 0$, generate randomly N position and heading particles $\mathbf{x}^i_0$ and an equal weight w^i_0.
- **Step 2. Prediction**: determine a new position of each particle based on walking direction θ_k and walking length L_k with a different noise realisation. The motion model for each particle at step k is shown in equation 5.
- **Step 3. Correction/Observation**: the weights update equation is:
$$w^i_k = w^i_{k-1} p(z_k|\mathbf{x}^i_k) p(\mathbf{x}_k|\mathbf{x}_{k-1}), \tag{12}$$
where $p(\mathbf{x}_k|\mathbf{x}_{k-1})$ is checking information between the new position and the map information to make sure whether the wall is crossed or not. It is equal to 0 if crossing a wall is impossible and 1 if possible. Then, normalise the weights: $\bar{w}^i_k = \frac{w^i_k}{\sum_{j=1}^{N} w^i_k}$, $i = 1, ..., N$. From the fingerprinting approaches, a position denoted z_k can be calculated by RSS measurements. The probability distribution $p(z_k|x^i_k)$ can be estimated as:
$$p(z_k|\mathbf{x}^i_k) = \frac{1}{\sqrt{2\pi\sigma^2}} exp(-\frac{||\mathbf{x}_{wifi} - \mathbf{x}^i_k||^2}{2.\sigma^2}), \tag{13}$$
where $\mathbf{x}^i_k$ is the position of the i^th particle at time step k, σ^2 is the variance based on the error of WiFi fingerprinting. Then, the state estimation can be determined by:
$$\hat{\mathbf{x}}_k = \frac{1}{N}\sum_{i=1}^{N} \mathbf{x}^i_k \bar{w}^i_k. \tag{14}$$
- **Step 4. Resampling** : generate a new set of particle $\{\mathbf{x}^i_k\}^N_{i=1}$ by resampling with replacement N times from $\{\mathbf{x}^j_k\}^N_{j=1}$, with probability $p\{\mathbf{x}^i_k = x^j_k\} = \bar{w}^i_k$ and using a Sequential Importance Resampling (SIR) [17], which tries to estimate the probability distribution.

III. Experimental Results

In this section, we evaluate the effectiveness of our improved framework. Our experiments are performed in two different test-beds to evaluate the performance of different WiFi techniques (GP and KNN in [13]) and compare the effectiveness of the proposed framework with WiFi fingerprinting and PDR, respectively.

A. Experimental setup

The first test-bed was at our laboratory room with size $11m \times 9.5m$, using three access points that are created by a WiFi module signal broadcast every 500ms. The training positions as testing data are collected by an application using a Samsung SG-G395F running Android 8.0.0.

The second test-bed was on the fifth floor of Krona building in University of South-Eastern Norway (USN) with size $56.1m \times 61.5m$, as shown in Fig. 4. The training data was placed 2.0 meters apart along the corridors. RSS and values of accelerometer and gyroscope were collected using a data logging application running on the smart-phone while the user was walking on the specific trajectory. Then, this data was saved to a CSV file for experimental evaluation.

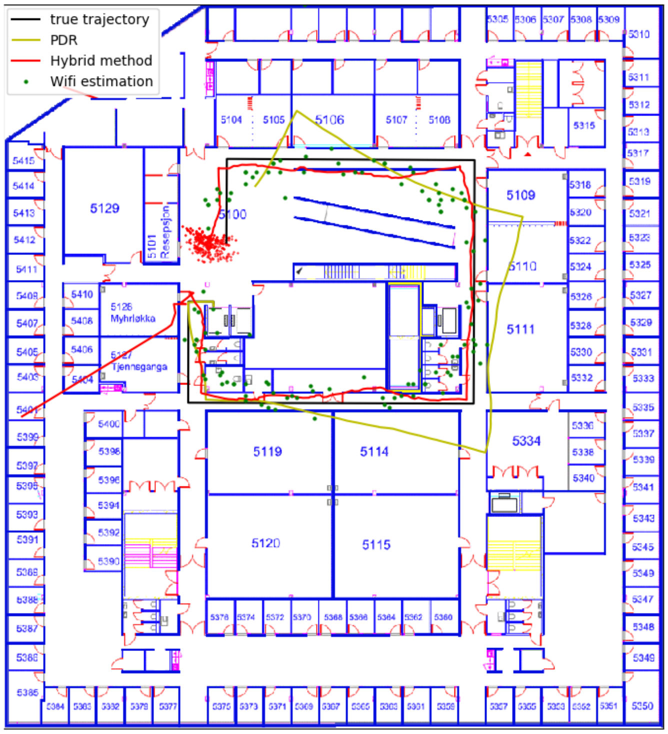


Fig. 4: The map for navigation user position considered for test-bed 2. The trajectory results of 3 different methods along the corridors are shown.

B. Experiment Evaluation

Two metrics are used to evaluate our framework:

- Accuracy: use root mean square errors of the estimated position and real position.
- Precision: it is consider how consistently the system works i.e the robustness of position techniques. A Cumulative probability function (CDF) of the distance error is used to measure the precision of the system [9].

1) Test-bed 1: evaluation of sparse training data for WiFi fingerprinting: Data set of training points were experimented two maps in our laboratory room: map-1 consists of 48 samples data spatially distributed with $1.5m \times 1.5m$ grid spacing; map-2 consists of 12 samples data spatially distributed with $3m \times 3m$ grid spacing. The results of two experiments with 22 testing samples is presented in Table I. Regarding map-1, the mean errors of the GP method are slightly lower than the KNN method. However, the position error confidence probability within 80% is approximately $2.7m$ for both methods, as shown in Fig. 5a. In the case of map-2 with sparse samples data , the average error of the GP method is $2.05m$, while the average error of KNN is $2.3m$. Furthermore, at the same 80 % of error confidence probability, the error of KNN is about $3m$, which is near 0.6 m higher than the error of GP, as shown in Fig. 5b. The results are shown in Table I. These results show that the GP is able to accurately extrapolate the signal strength model into the points for which no training data is available at all.

2) Test-bed 2: Comparison between the hybrid method with WiFi fingerprinting and PDR: The trajectory results for three different methods are shown in Fig. 4. The corresponding cumulative distribution function of total positioning errors for the three approaches are illustrated in Fig. 5c. The mean errors of the three methods are shown in Table II. The green points are the results from GP fingerprinting, the mean error is $2.62m$ and mean error of the PDR method is $3.9m$ because of inaccurate heading estimation during walking. While the hybrid method can obtain a mean error of $1.17m$ by using 500 particles combined with checking walls from the map and without an initialised start point. The trajectory is converged after a few steps relied on WiFi estimation and wall-crossing detection. The average positioning accuracy of the proposed framework was reduced by 48% and 70% compared with the WiFi fingerprinting and the PDR method.

method	mean errors ($1.5m$)	mean errors ($3m$)
GP	1.762	2.05
KNN [13]	1.86	2.3

TABLE I: Mean errors of two different method using training data spatially distributed with $1m$ $1m$ and $3m \times 3m$ grid spacing.

	WiFi with GP	PDR	Hybrid
Mean errors (m)	2.62	3.9	1.17

TABLE II: Result of mean errors for GP, PDR and Hybrid method

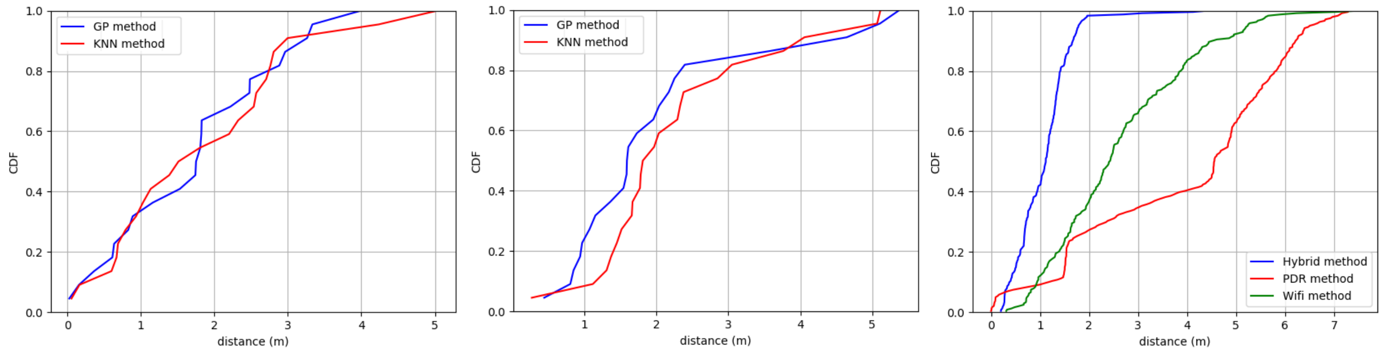
Considering the computational time of the particle filter, different experimental results are shown in Table III. The higher number of particles for the filter reaches better accuracy. However, the computational time is also higher. Constraining the wall penetration of each particle reduces computation time. In order to reduce computation cost on the smart-phone, a server was built by using a Sailjs MVC framework [18] running on a laptop. All of the databases of the WiFi fingerprinting map and building map are stored on the server using MySQL.

IV. Conclusion and Future Work

In this paper, we proposed a framework that combines WiFi fingerprinting methods and Pedestrian Dead Reckoning (PDR) by using a particle filter. The Gaussian Process Regression for WiFi fingerprinting is deployed to generate a WiFi map that can partially reduce the time of training data and high accuracy for indoor environments. The proposed hybrid approach makes it possible to address the well-known drift problem of the PDR approach. This is possible by combining the PDR with fingerprinting so that high accuracy can be achieved in a certain area based on the Received Signal strength (RSS). This approach also has the advantage that it can be easily deployed

Method	Computation Time (ms)	Particles
PDR + GP	58	200
PDR + GP + map	85	200
PDR + GP	220	500
PDR + GP + map	278	500
PDR + GP + map	830	1000

TABLE III: Results of the implemented hybrid methods considering the number of particles used in the filter and the corresponding computational time.



(a) CDF of errors of two methods using map-1 of test-bed 1

(b) CDF of errors of two methods using map-2 of test-bed 1

(c) CDF of the location errors for the three approaches of test-bed 2

Fig. 5: Cumulative probability functions results of experiment

in real situations. Moreover, a particle filter is leveraged in our proposed framework to update each particle based on the PDR motion model by using effective algorithms for step detection, stride length and heading. Then, the position of WiFi fingerprinting estimations is combined with feature maps for each particle correction. The experiments were conducted in a real building without additional infrastructures. The results in experiments indicate the effectiveness of our proposed framework.

The accuracy of our proposed framework also depends on the features of indoor environments (e.g. narrow corridors with walls), drifting value of the PDR method and the number of access points. In future works, we will attempt to combine extra information (i.e. landmarks) to achieve a higher localisation accuracy. In this work, the stride lengths are computed for offline calibration. thus, we will consider calibrating these parameters while people are working inside the building.

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