Fusing Map Information with a Probabilistic Sensor Model for Indoor Localization using RF Beacons

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Abstract*—Accurate localization is a fundamental requirement for a variety of applications, ranging from industrial robot operations to location-powered applications on mobile devices. A key technical challenge in achieving this goal is providing a clean and reliable estimation of location from a variety of low-cost, uncalibrated sesnors. Many current techniques rely on Particle Filter (PF) based algorithms. They have proven successful at effectively fusing various sensors inputs to create meaningful location predictions. In this paper we build upon this large corpous of work. Like prior work, our technique fuses Received Signal Strength Indicator (RSSI) measurements from Bluetooth Low Energy (BLE) beacons with map information. A key contribution of our work is a new sensor model for BLE beacons that does not require the mapping from RSSI to distance. We further contribute a novel method of utilizing map information during the initialization of the system and during the resampling phase when new particles are generated. Using our proposed sensor model and map prior information the performance of the overall localization is improved by $1.20\,\mathrm{m}$ on comparing the 75th percentile of the cumulative distribution with traditional localization techniques.

Keywords: Localization, Bluetooth Low Energy (BLE), Map Priors, Sensor Modeling

I. Introduction

Localization and navigating using Global Navigation Satellite System (GNSS) has become an essential enabler in many of today's popular mobile applications and experiences. However, GNSS is often not available indoors and hence poses challenges in achieving accurate, ubiquitous localization in these environments. Researchers have developed different localization solutions that utilize varied sensors including RGB-D cameras [1], Inertial Measurement Unit (IMU) [2], and radio ranging over wireless access points (Wi-Fi) [3] and Bluetooth Low Energy beacons (BLE) [4], [5]. Additionally, researchers have also focused on developing multi-sensor localization approaches by fusing two or more sensors [6], [7], [4].

Our work makes use of radio-based (RF) technologies. We believe that RF has many practical advantages. For instance, the radios leveraged in our techniques are common and ubiquitous on today's modern devices. Further, these technologies have duality of purpose, providing communication and interaction capabilities for the blossoming Internet of Things (IOT) revolution. Many solutions, including our own, leverage the saturated ubiquity of Bluetooth Low Energy (BLE) technology [4], [5] and/or Wi-Fi [8] to utilize the Received Signal

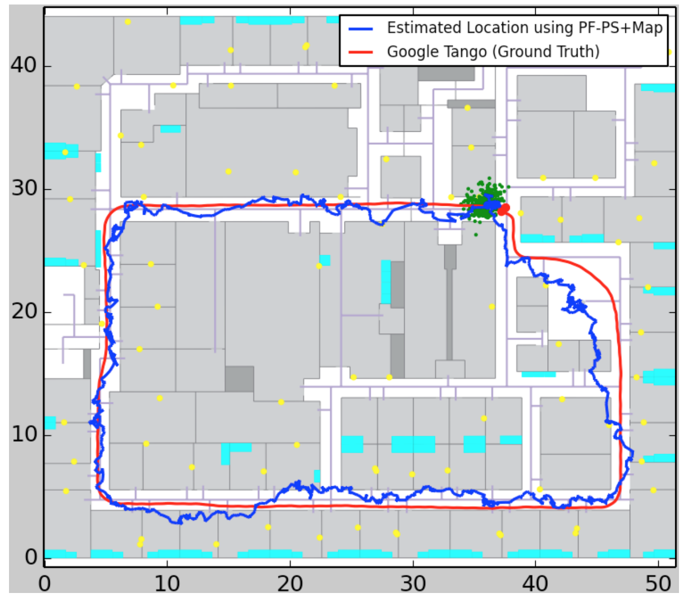

Fig. 1: Comparison of indoor positioning results of Particle Filter using Probabilistic Sensor and Map information (PF-PS+Map) with ground truth. The yellow dots represent the location of the beacons deployed in the environment. The purple lines corresponds to the navigation paths between different rooms.

Strength Indication (RSSI) to estimate a device's position. While indoor radio propagation can be modeled accurately in controlled environments, indoor environments present many physical challenges, e.g., the presence of tinted metal in windows, that make modeling the radio signal attenuation significantly more challenging [9]. Traditional RF-based localization techniques map RSSI to distance using the Friis free space model [4]. However, the assumption in the Friis model that the medium of signal propagation is uniform is violated for indoor environments and hence does not provide optimal mapping from RSSI to distance.

In this paper, we propose a novel probabilistic sensor model that utilizes raw RSSI within the position estimation system. The use of RSSI measurements removes the non-linearity and/or bias introduced by the RSSI-to-distance converter using Friis free space model. Further, we also propose a technique to utilize map information within our localization

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framework to improve the overall localization accuracy. The motion of a smart device user can be constrained using the map information allowing the system to accommodate for situations such as restricting the user from passing through obstacles such as walls, partitions, etc. Both techniques are utilized during different phases of particle filter framework to estimate the location of a smart device user. Our proposed technique consisting of fusing map information with RSSI received from BLE beacons provides an improvement in the overall localization accuracy by 42% when compared with traditional techniques as reported in our previous work [5]. For completeness we also compared the improvement in accuracy provided by each module, i.e., the probabilistic sensor model and map information when utilized within the PF framework.

Rest of the papers is organized as follows: In the next section we present the related work. In Section III, we formulate the problem and explain other assumptions. In Section IV and Section V we present details of our proposed sensor model and how map information is utilized within our proposed framework. Lastly, we present our experimental results in Section VI followed by discussion and conclusion in Section VII and Section VIII respectively.

II. Related Work

Indoor localization using RF beacons is not a new idea; it has been extensively studied in the robotics and sensor network communities. Solutions include fingerprinting the environment [4], [10], [8], Bayesian filtering approaches [5], [11], [12], [13], and sensor fusion [14], [7], [15].

A. Fingerprinting Based System

Fingerprinting the environment to generate a signature map for RSSI signal is a common approach [4], [12], [10]. The central principle of this method is to compare the a sampled vector of RSSI at a given location with the pre-recorded fingerprint of the environment stored in the database. The matching is performed using various kernel methods in the form of Support Vector Machines (SVMs), K-Nearest Neighbour (K-NNs) framework, or parametric methods such as Hidden Markov Model (HMM). In [10], Ma *et. al.* proposed a RSSI ranking based fingerprinting method that uses Kendall Tau correlation coefficient to correlate the position with the signal strength ranking of multiple BLE devices deployed in a given environment. Similarly, Faragher and Harle used a fingerprinting technique to analyze the performance of BLE based localization using K-NNs and proximity-based techniques [4]. However, these approaches require the tedious process of mapping the RSSI values in different locations in the environment. Furthermore, the likelihood map is non-adaptive and does not take into account the dynamic of the environment such as reflection and multipath issues of RSSI.

B. Model Based System

In model based localization systems, the propagation of raw RSSI through a space is modeled using various techniques such as Friis free space model [16], Gaussian processes [5], or Wasserstein distance model [17]. The sensor model is further utilized within different probabilistic frameworks to estimate the location of the user. A Kalman filter was proposed by Sung to reduce the noise in the log distances determined by a path loss model from the RSSI [18]. Danis and Cemgil proposed a Wasserstein distance interpolation to convert the BLE signal to range. This is further combined with the Sequential Monte Carlo (SMC) method for tracking [17]. In our previous work [5], we proposed a Gaussian Process (GP) based classifier to classify whether a given signal is within bounds of the BLE sensor model. The classifier was utilized by the particle filter framework to use or discard a given BLE signal. While these techniques are considered the state-of-the-art in RF-based localization, RF-models alone often fail spectacularly in the context of various physical limitations, e.g., localizing to a non-accessible position.

C. Multiple Sensor Fusion Based System

To overcome limitations inherent to a single approach, researchers have investigated fusing RF sensor with various other sensors such as Inertial Measurement Unit (IMU) [15], [7] or prior map information [13]. Wang *et. al.* developed a system that fuses Wi-Fi signal propagation with IMU sensors using a Kalman Filter (KF) to provide highly accurate localization and tracking. Similarly, Yoon *et. al.* proposed a KF-based system that fuses RSSI signal from BLE with IMU measurements that are further smoothened using Rauch-Tung-Striebel smoother. Perera *et. al.* used map prior information along with Wi-Fi fingerprinting to estimate the location of the user in a shopping mall. The Wi-Fi fingerprint matching is done using Kernel Density Estimator (KDE). Lastly, in [19] the author uses the floor plan to associate multipath components of the propagated radio signal to the surrounding geometry. An environment survey prior to the experiment is required along with more sophisticated hardware for data collection.

Our proposed system is a multi-sensor fusion system that utilizes RSSI signals from BLE beacons deployed in a given environment and fuses them with map information using the particle filter framework. The system is built using a novel probabilistic sensor model that uses the raw RSSI signal as a proxy rather then using RF propagation model to convert RSSI to range. Our proposed sensor model eliminates the use of the RF propagation model as its properties are not withheld by the environment. Further, in order to align the localization system with the normal and expected motion users, such as entering rooms through doors and not through walls, we utilize map information in multiple stages of estimation (described in detail in Section III). We note that utilizing map information within a Bayesian filter framework has been performed for sensors such as ultrasound and infrared [20], [21], [22]. To the best of our knowledge, the map aid technique proposed in [22] is conceptually the closest to this work, but our proposed particle projection technique and its utilization within the particle filter framework differs from that technique. The contribution of our proposed approach can be summarized as follows:

i. We propose a probabilistic sensor model to accommodate for noisy RSSI signal received from the BLE beacons. Our proposed sensor model utilizes the raw RSSI value and compares it with the expected RSSI to estimate the confidence of a given measurement. This confidence score is further used during the measurement update phase of the PF.
ii. We also propose a method to utilize the map information of a given environment within the PF framework. Utilizing map information further enables the localization system to follow the motion behavior of the user, i.e., a user will enter a room through a door and not a wall. The novelty of our method is the way in which map information is utilized within the PF framework. Our method constrains the motion of the particles by projecting the newly generated particles on the navigation routes and/or rooms. Our method further ensures that the probabilistic properties of the PF is maintained.

III. Proposed Methodology

Our proposed localization system consists of RSSI observations that are non-linear in nature and the posterior density is often multi-modal. Hence we formulate our problem using a Particle Filter (PF) approach that is a non-parametric implementation of the Bayes filter and suitable for tracking and localization problems where dealing with global uncertainty is crucial [23]. We utilize a Sample Importance Resampling (SIR) filter embedded with the systematic resampling algorithm. To detect the degeneracy and perform resampling, we compute the effecting sample size that corresponds to the reciprocal of the sum of squares of particle weights.

We define the problems within the paradigm of the particle filter and briefly explain the preliminaries to solve these problems. Let $\mathcal{M} = \{\boldsymbol{m}^{[j]}\}_{j=1}^{n_m}$ be a set of known and fully observable features whose elements, $\boldsymbol{m}^{[j]} \in \mathbb{R}^3$, represent BLE beacons locations. The receiver (smartphone user in our case) can only receive the RSSI signals that are broadcasted by the BLE beacons. Let $\mathcal{S}_t \subset \mathbb{Z}$ be the set of possible RSSI measurements at time t. The observation consists of an n_s-tuple random variable $(S_t^1, ..., S_t^{[n_s]})$ whose elements can take values $\boldsymbol{s}_t^{[k]} \in \mathcal{S}_t$, $k \in \{1, ..., n_s\}$. We denote the position up to time t by $\boldsymbol{x}_{0:t} \triangleq \{\boldsymbol{x}_0, ..., \boldsymbol{x}_t\}$ where $\boldsymbol{x}_t \in \mathbb{R}^3$. Given the set of known BLE beacons and noisy observations, we wish to solve the following problems.

Problem 1 (Measurement model): Let $\mathcal{Z}_t \subset \mathbb{R}_{\geq 0}$ be the set of possible RSSI measurements at time t that are received from z_t number of BLE beacons. The measurement model $p(z_t|\boldsymbol{x}_t)$ is a conditional probability distribution that represents the likelihood of RSSI measurements. Further, the proposed function should also incorporate the measurement noise appropriately.

Problem 2 (Positioning): Let $z_{1:t} \triangleq \{z_1, ..., z_t\}$ be a sequence of range measurements up to time t. Let $\boldsymbol{x}_t$ be a Markov process of initial distribution $p(\boldsymbol{x}_0)$ and transition equation $p(\boldsymbol{x}_t|\boldsymbol{x}_{t-1})$. Given the measurement model $p(z_t|\boldsymbol{x}_t)$, the objective is to estimate recursively in time the posterior distribution $p(\boldsymbol{x}_{0:t}|z_{1:t})$.

As a solution to the first problem, we try to characterize the RSSI values received from beacons through an appropriate sensor model. Our proposed sensor model is a probabilistic distribution that encapsulates the RSSI behavior of the signal propagation in a given environment. Furthermore, the sensor model also accounts for the inherent measurement noise present in the RSSI signal. Details of our proposed sensor model can be found in Section IV.

The second problem can be seen as a localization problem that can be solved using the PF framework. To further improve the accuracy of the position estimation, we utilize map information during different stages of PF. Detailed description if this technique is listed in Section V. It should be noted that the map information is used to constrain the motion of the particles that in turn assists in improving the overall position estimates.

We use the following assumptions for the BLE beacons used for localization. For simplicity, since the locations of the BLE beacons are known, they are eliminated from conditional probabilities terms.

Assumption 1 (Constant transmission power): The transmission power of all beacons during positioning experiments remains fixed.

Since a different transmission power leads to a different signal propagation behavior, i.e., a shorter or a longer range, this assumption guarantees that the sensor model complies with the employed beacons.

Assumption 2 (Known data association): Each beacon has a unique hardware identifier that is available to the receiver device.

This is normally the case in practice as the unique MAC-address of each beacon is broadcasted along with the RSSI values. Hence, this assumption relaxes the need for data association. Finally, we assume that the only available information to the receiver is the RSSI. This is the common case for existing wireless routers and BLE beacons. However, if the time difference of arrival (transmission time) is available to the receiver device, the position estimation accuracy can be improved.

Bluetooth low energy technology

The Bluetooth Low Energy [24] protocol was devised in 2010. It operates in the 2.4 GHz license-free band and hence shares the same indoor propagation characteristics as 2.4 GHz Wi-Fi transceivers. Unlike Wi-Fi, BLE uses 40 channels, each with a width of 2 MHz [4]. BLE advertising beacons are particularly attractive to retailers because of the promise of long battery lives of many years and hence have low maintenance requirements. Long battery lives are expected to require low radio power output and/or low beaconing rates. While this does not affect their use for proximity detection, it does affect their usefulness for indoor positioning systems.

IV. Probabilistic Sensor Model

Traditionally, RSSI based sensor model utilize the Friis free space model [16] to map the RSSI measurements to distance.

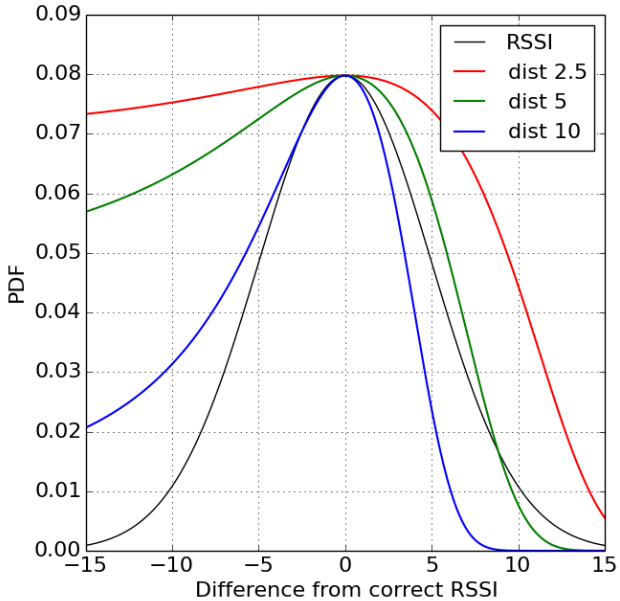


Fig. 2: PDF when assuming a Gaussian distribution of linear distance errors with the same standard deviation at different distances. σ is 5dB and 5m, respectively.

This RF propagation model assumes that the medium in which the signal propagates is uniform. The equation of calculating distance from RSSI is as follows:

$$p_{RSSI} = a_X + 10\gamma \log_{10}(z) + \epsilon \tag{1}$$

where, a_X in dBm, is the RSSI at a distance of $1\,\mathrm{m}$ [1], p_{RSSI} in dBm, γ is the path-loss exponent and ϵ is the received signal power noise and assumed to have an independent and identically distributed (i.i.d.) Gaussian distribution.

The conversion from RSSI to distance specified in Equation 1 is normally not valid for indoor environment that consists of walls, windows, partitions, doors, etc. This further impacts the propagation of RF signals that is not accounted for by the traditional RF propagation model.

Further, statistically evaluating the RF propagation model that converts RSSI to range assume implicitly that the error is normally distributed. However, this assumption is contradicted when comparing the range generated from the RSSI measurements with the ground-truth distance. On the contrary, the error of the measured RSSI value against the RSSI value predicted by the path loss model from the a specific ground truth distance is normally distributed. Even for different distances, the standard deviation of this error is the same, about 5 dB in our office space (illustrated by the black curve in Figure 2).

A normal distribution of the the RSSI error implies a normal distribution of the error of the log distance. However, the error of linear distance has a different distribution. Figure 2 illustrates what happens if one assumes a normal distribution of the linear distance error. The Probability Density Function (PDF) of the error of RSSI is included with the same σ to better illustrate the difference. When converting the difference the linear distance back to RSSI, one can see that the distribution of the PDF is not Gaussian. For example, at an actual distance of 2.5 meters from the beacon, an RSSI value 15 dB higher than the predicted value corresponds to a predicted distance of 0.44 meters (factor of 5.6). This is an error of 2.06 meters of the linear distance. With a σ of 5 meters, this only deviates by 0.41 standard deviations from the predicted value so that the PDF is high. When looking at the same situation at an actual distance of 10 meters from the beacon, the same RSSI increase of 15 dB corresponds to an error of 1.64 standard deviations in the linear distance with a correspondingly lower PDF. On the flip side, with an RSSI decrease of 15 dB, the error of linear distance is 2.8 and 11.2 standard deviations, respectively, for the actual distances of 2.5 and 10 meters. That means that an erroneous location close to a beacon will be given a higher weight than a location with the same linear distance error far from a beacon. Also, the curve is not symmetrical, assigning higher weights to shorter distances.

We address this issue in our model by converting the distance from a beacon to a location to be evaluated (particles of PF in our case), to an expected RSSI value ($\hat{p}_{RSSI}$) using Equation 1. The difference between the expected and actual RSSI value are further used to sample the weight of the particles from a given PDF described as follows:

$$p(w^{[i]}) = \mathcal{N}(0, \sigma_s^2) \tag{2}$$

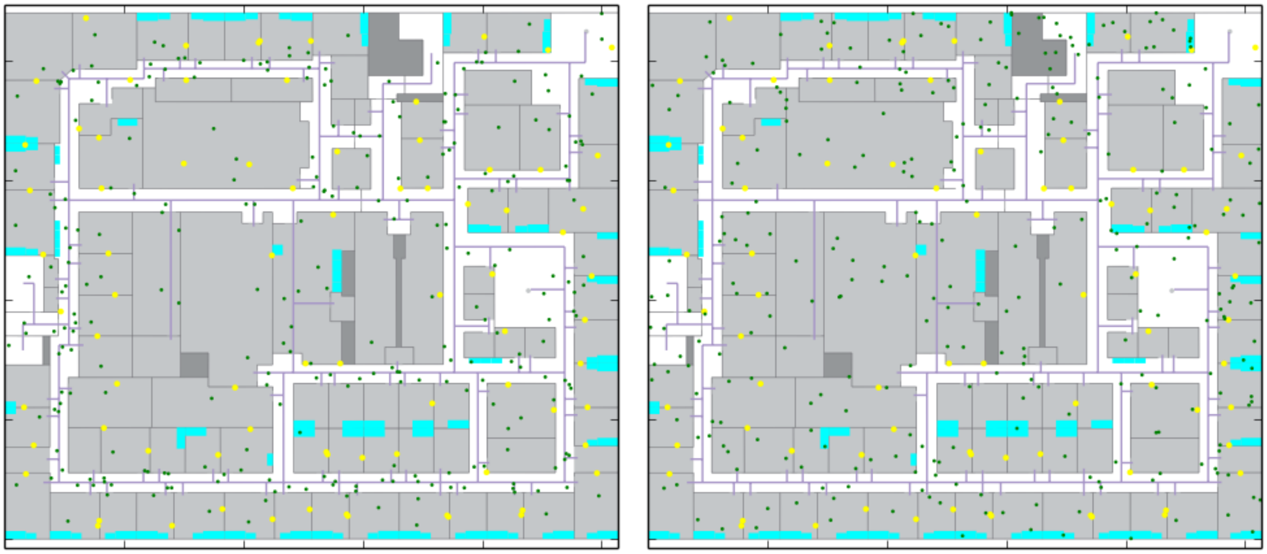
V. Fusing Map Information

Map information of a given environment is normally available for various public and office buildings. This provides important information such as location of rooms and corridors, entrance doors, etc. This information can be exploited further so that a user's motion behavior in a given environment can be encapsulated within the localization system.

To elaborate this with an example, consider a scenario of user walking from one room to another. The normal pattern of the user would be to walk out of the door of a given room and walk through the corridor to reach the next room where the user will enter through the entrance door. To incorporate this behavior, we divide the environment into rooms and navigational routes between these rooms. The navigational routes can be visualized as a connected graph (illustrated by purple lines in Figure 3) whereas the rooms can be seen as bounded boxes (illustrated by grey boxes in Figure 3). Within the PF framework, we utilize this information during the initialization of the particles and during the resampling phase of the PF. It should be noted that the map information is utilized such that properties of the PF are maintained.

During the initialization of PF, we condition the distribution of particles around the edges of the navigational routes and in rooms. This inherently helps in constraining the initial distribution of particles to areas where a user is more likely to visit or to walk through. Further we divide the distribution

[1] As specified in the iBeacon protocol.



(a) (b)

Fig. 3: Comparison of initialization of particles with and without using map information. In (a), the particles are initialized using the map information and are distributed in rooms and on the navigational edges based on the ratio β. Further the particles are also proportionately distributed based on the areas of the rooms and the lengths of the navigational edges. In (b), particles are randomly initialized over the the entire map.

of particles spread around navigational edges and rooms by a ratio β. The initialization particles using our approach can be defined as follows

$$p(\boldsymbol{x}_o^{[total]}) = \\ (p(\boldsymbol{x}^{[\beta * i]}|m_n) + \mathcal{N}(0,\, \sigma_{nav}^2)) + \\ (p(\boldsymbol{x}^{[(1-\beta)*i]}|m_r) + \mathcal{N}(0,\, \sigma_{rm}^2)) \tag{3}$$

where m_n and σ_{nav}^2 is the map info for edges of navigational routes and the standard deviation used for distributing particles around those edges, whereas m_r and σ_{rm}^2 is the same for particle distribution in rooms. Further, the particles are proportionately distributed in rooms and edges based on the size of rooms and lengths of the navigational edges. An example of particle distribution during initialization using our proposed system as compared to random distribution is shown in Figure 3. Further, conditioning the particles using the map information leads to faster convergence to true localization.

Resampling in PF is performed to effectively remove particles that are outliers and replace them with new particles that are initialized around the particles with highest weight. To detect the degeneracy of particles, we calculate the effective sample size, $n_{eff} = (\sum_{i=1}^{n_p} w_t^{[i]})^{-1}$, and perform resampling when $n_{eff} < n_{thr}$; where n_p is the number of particles and n_{thr} is a threshold $1 < n_{thr} < n_p$.

We utilize the map information during the resampling of particles and condition the newly generated particles using the same parameters as used during the initialization process. The newly generated particles are conditioned differently for new particles that are generated around the navigational edges as compared to those generated inside rooms. For navigational edges, the newly generated particles are projected back on the closest navigational edge by the shortest perpendicular distance. To deal with the particles in the room, each room is shrunk in size by $1\,\mathrm{m}$ from all the sides. This is used as a parameter for conditioning the particles that are generated in the room. If the newly generated particle is located within the shrunken area of the room, then those particles are not conditioned any further. Particles on the periphery of the shrunken area are projected back on to the closest edge of the shrunken area. Each of these condition can be defined as follows.

$$p(\boldsymbol{x}_{new}^{[i]}) = p(\boldsymbol{x}_{stg}^{[i]}) + \mathcal{N}(0,\, \sigma^2) \tag{4}$$

where $x_{new}^{[i]}$ is the newly generated particle and $x_{stg}^{[i]}$ is the particle with strongest weight.

$$p(\boldsymbol{x}_{new}^{[i]}) = \\ \begin{cases} p(x_{new}^{[i]}|m_n) & \text{if } x_{new}^{[i]} \text{ is close to navigation route} \\ p(x_{new}^{[i]}) & \text{if } x_{new}^{[i]} \text{ is in the shrunken room} \\ p(x_{new}^{[i]}|m_r) & \text{if } x_{new}^{[i]} \text{ is near the edge of shrunken room} \end{cases} \tag{5}$$

Our proposed system utilizes the map information only during the initialization of the particles and during the resampling of new particles. This assures that the overall PF framework is a measurement only system that estimates the position of user using only the BLE measurements.

VI. Experimental Setup & Results

We evaluate the performance of our proposed system that utilizes a probabilistic sensor model and map information (PF-PS+MAP) withing a particle filter framework. We tested our

TABLE I: Parameters used in the experiments

Parameter	Symbol	Value
– Compared SIR particle filter variants:		
Path-loss measurement model	PF-PL	-
Path-loss with Map information	PF-PL+MAP	-
Probabilistic measurement model	PF-PS	-
Probabilistic measurement model with Map information	PF-PS+MAP	-
– Path-loss model parameters:		
Unit power at 1m (ibeacon protocol)	a_X	-60.00
The path-loss exponent	γ	2.25
– Measurement model:		
standard deviation (PF-PL)	σ_n	6 m
standard deviation (PF-PS)	σ_s	6.85 m
– Initialization:		
standard deviation for nav. particle distribution	σ_{nav}	2 m
standard deviation for room. particle distribution	σ_{rm}	1 m
ratio of particle distribution	β	0.80
– Motion model:		
Position standard deviation	σ_u	0.1 m
Velocity standard deviation	σ_v	0.1 m / sec
– Particle filter:		
Number of particles	n_p	300
Resampling threshold	n_{thr}	0.80
– BLE Beacon Parameters:		
Transmission Power	–	+4 dBm
Max RSSI Threshold cut-off	–	-95 dB
Broadcasting Frequency	–	10 Hz

system on a dataset collected locally in our office space that spans over $2200\,\mathrm{m}^2$. For completeness we also compare accuracy achieved using our technique with other traditional sensor model (Friis free space model) (PF-PL+MAP) in presence of map information. Lastly, we evaluate the importance of map information by testing both the sensor model in absence of map information (PF-PL & PF-PS).

A. Dataset

We collected a large indoor dataset in our office space of size $45 \times 55\,\mathrm{m}$, that consists of typical office furniture, corridors, offices, desks, chairs (office floor plan shown in Figure 1). We installed 79 BLE beacons at different locations in the office such that RSSI signal is received from at given location. Details of installation of beacon points is shown in Figure 3a (denoted by yellow dots). Data was collected using an Android application developed in-house that was installed on a Nexus 6P smartphone[2]. The Android application continuously scanned for BLE beacons that were deployed in a given environment. The BLE scans are sampled at $10\,\mathrm{Hz}$; however, in practice, we experienced an average sampling rate of $7\,\mathrm{Hz}$. For ground truth, we used a Google Tango device [25] that provides the trajectory estimate using visual-inertial odometry. We recruited a user who was not aware of the functioning of our proposed system. The user was given instruction of the path to follow before hand and was asked to walk at a speed consistent with their normal, everyday activities. The user walked around $200\,\mathrm{m}$ in a predefined path in the office space. The BLE scan data collected by the smartphone was later synced with ground truth trajectory data using time stamps. Note that data is collected in a natural setting on a normal working day and in presence of office staff members with no movement restrictions to staff members[3].

[2]https://www.google.com/nexus/6p/

[3]The dataset is available upon request. Please contact the authors.

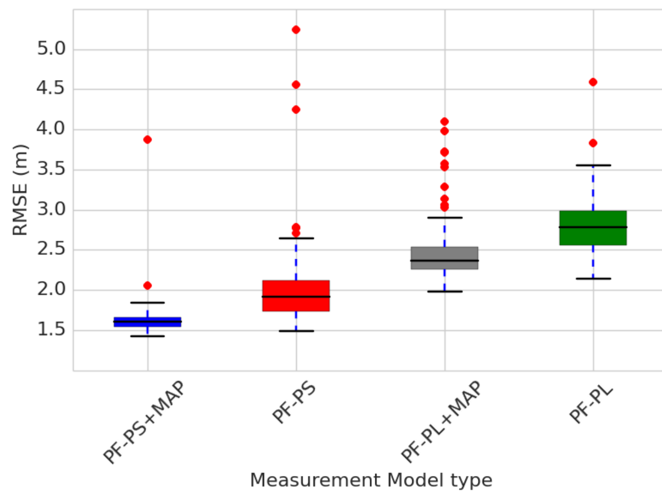


Fig. 4: Indoor positioning results from 100 independent runs using different combination of measurement and sensor model. The average RMSE error using combined probabilistic sensor model with map information is in the range of 1.6 m as compared to other sensor combination.

B. Results

In all experiments the number of particles were fixed to 300. In order to accommodate for the non-deterministic nature of PF, we evaluated the results from 100 independent runs on the collected dataset. Details of different parameters used in our experiments is listed in Table I. The average RMSE error of PF using our proposed sensor model and map information (PF-PS+MAP) was $1.635\,\mathrm{m}$ where as the same using $2.481\,\mathrm{m}$ using the traditional sensor model(PF-PL+MAP). Trajectory plot from one of the PF evaluation using our proposed system (PF-PS+MAP) is shown in Figure 1. In absence of map information, the average RMSE error using our proposed sensor model was $2.042\,\mathrm{m}$ where as the same was $2.813\,\mathrm{m}$ using the traditional sensor model, that further substantiates the fact that our proposed sensor model is more aligned with the RSSI signal behavior. Lastly, the improvement in the accuracy by incorporating the map information further validates our hypothesis that user motion can better be modeled by the PF framework in presence of map as it intuitively constrains the motion to the areas where the user is most likely to visit. The statistical summary of the results for all the four experiments over 100 independent runs is shown in Figure 4 and listed in Table II.

Figure 5 shows the empirical cumulative distribution function (CDF) of the compared techniques. The empirical CDF is an unbiased estimate of the population CDF and is a consistent estimator of the true CDF. Note that faster rise from zero to one along the vertical axis is a desirable outcome. Using the evaluation method from the EvALL competition [26], the error over the third quartile is around $1.6\,\mathrm{m}$ for our proposed system (PF-PS+MAP) whereas the same is $2.7\,\mathrm{m}$ (PF-PL+MAP). Video for one of the PF evaluation using our proposed system

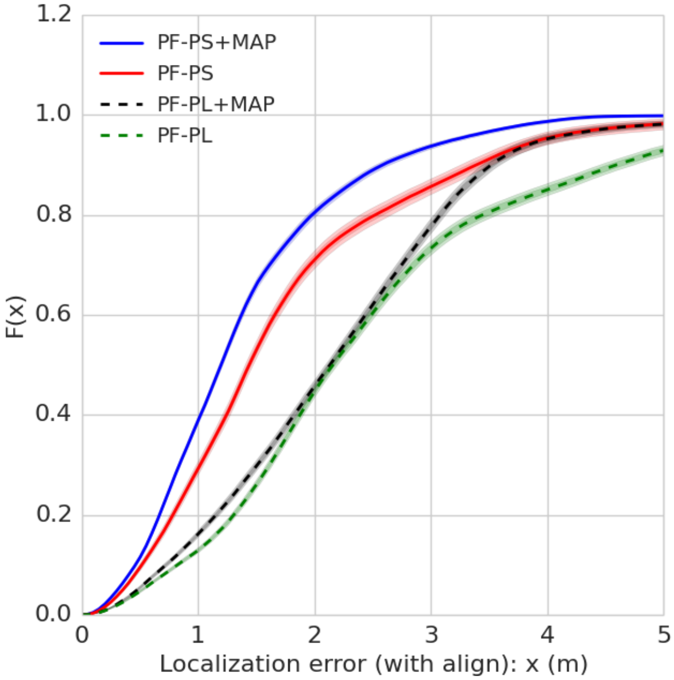


Fig. 5: Comparison of the empirical cumulative distribution function using our proposed Probabilistic-sensor model with Map priors (PF-PS+MAP) with traditional Path-loss model (PF-PL+MAP) and the same when map prior information is not used. The plot display the average CDF from 100 independent runs and 95% confidence bounds.

can be found at the attached link[4].

C. Computational Efficiency

Utilizing map information provides computational challenges as the new particle needs to be either aligned to navigational edges or to edges of the shrunken bounded boxes of the rooms. This requires computing the perpendicular distance of each new particle to all navigational edges and edges of the room containing the particle. In our map, we have 223 navigational edges and 95 rooms. In order to accelerate the computation, we first set the maximum distance at which we need to find an edge ($3\,\mathrm{m}$ for our experiments). We divide the map into grid structure with a spacing of one meter. Only edges close to a cell and rooms intersecting a cell are indexed from that cell. We only search for the closest edges and rooms in a given grid cell where the new particle is generated. This reduces the overall search space an average to 7.3 edges and 1.5 rooms as compared to 223 edges and 95 rooms. This is a substantial improvement that enables the use in a real-time system and further make our proposed system scalable to larger spaces.

VII. Discussion

The results presented in Section VI-B illustrate how our proposed system provides improvement in the localization accuracy when compared with other systems. The RSSI signal of BLE beacons are impacted by various environmental factors and hence does not provide reliable distance conversion. Our proposed sensor model does not require the mapping from RSSI values to distance and hence is better aligned with the behavior of the RSSI signal broadcasted by the BLE beacon in a real world scenario.

Further, by exploiting the map information of a given environment, the system provides better location estimates as it assists the PF in placing particles in areas where users is likely to visit or walk through. In our proposed approach, the map information is utilized only during the initialization of the particles and during the resampling of new particles. This intrusively constrains the motion of the particles keeping the estimates close to the navigational edges and/or rooms.

[4]https://youtu.be/3BK3ERiHB-M

TABLE II: Comparison of the results of indoor positioning with and without incorporating our proposed probabilistic sensor model and map information. The results are averaged over 100 runs; mean ± standard error.

Model	PF-PS+MAP	PF-PS	PF-PL+MAP	PF-PL
RMSE (m)	1.635±0.245	2.042±0.552	2.481±0.407	2.813±0.374
CDF (75 percentile)	1.60	2.0	2.7	2.8

A. Limitation

The main limitation of the proposed probabilistic sensor model is that the value of the RSSI signal received at a given distance varies with the transmission power (TP) of the BLE beacon. However, even when using beacons with different TPs, the performance may be similar as long as the RSSI has the same standard deviation at different power levels and the power level at one meter distance is properly calibrated. Secondly, RSSI values is the only information received from the BLE beacons with the existing Bluetooth protocol, hence the system is impacted for situations where the received RSSI values are impacted by factors such as Non Line of Sight (NLOS) and reflection from other environmental factors.

VIII. Conclusion & Future Work

In this paper, we propose a probabilistic sensor model that is fused with map information withing a PF based positioning system to estimate the location of smart device user in a given environment. The system utilizes the RSSI signals broadcasted by the BLE beacons deployed in a given environment. Our proposed probabilistic sensor model estimates the confidence of the received RSSI values at any given location thereby removing the mapping required from RSSI to distance. Lastly, we also provide a technique to influence the particles of PF by using the map information during different stages of the PF. It should be noted that the map information is utilized such that the overall PF can still be considered as a measurement only PF.

In the future, we plan to extend this work by fusing the other sensors such as Ultra Wide Band (UWB) with BLE sensors, thereby mitigating some of the limitations of BLE beacons. UWB sensors provides time difference of arrival information to the receiver device that can lead to better position accuracy. UWB has its own limitation in terms of power consumption as compared to BLE beacon hence, fusing a limited number of UWB sensors with BLE beacons would lead to reduced power consumption and improve the overall position accuracy.

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