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ORIGINAL ARTICLE

Using phase shift fingerprints and inertial measurements in support of precise localization in urban areas

Mohammed Elbes[1] · Ahmad Alkhatib[2] · Ala Al-Fuqaha[3,4] · Junaid Qadir[5]

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Abstract

Localization is an important primitive that is utilized in a number of important applications such as location-based mobile services, augmented reality, and autonomous mobile robotics. While the GPS technology is considered the de facto standard for outdoor localization, it is known to suffer from significant accuracy limitation in urban areas. In this work, we present a particle filter–based data fusion technique for localization in urban areas. The proposed localization technique provides more accurate location estimation results due to its ability to efficiently fuse together information collected from diverse sensor technologies. The novelty of our proposed approach stems from its ability to fuse data from diverse sources, namely, phase shift fingerprints collected from Low Power AM Radio (LPAM) towers and inertial measurement sensors. Our simulation results indicate that the proposed approach can achieve an accuracy of 0.5 m using a limited number of LPAM towers as low as 5. Also, the proposed approach requires the collection of a low number of LPAM phase shift fingerprints. Our simulations indicate that 30 fingerprints are enough to provide 0.5 m accuracy in a $100 \times 100\ m^2$ deployment.

Keywords Smart cities · Localization in urban areas · Data fusion · Fingerprinting · Channel state information

1 Introduction

In recent years, several critical national infrastructures (such as the electric grid, intelligent transportation, water systems) are becoming smart in many aspects. The concept of smart cities is gaining increased importance as a means towards making services and applications more accessible to citizens, companies, and organizations. A smart city's target is to increase citizens' quality of life, improve the efficiency, and the quality of the services provided by governing entities and businesses provide intelligent responses to different issues of the rapid urban population growth.

In such applications, the provision of location-based services is attractive for many reasons. Many smart city applications can benefit from localization such as localizing forest fire [1, 2], smart transportation and mobility systems [3], location-based services in 5G cellular system [4], ambient-assisted living (AAL) tools and health monitoring applications [5], elderly care and movement/activity detection [6], smart buildings [7], and smart waste [8].

Positioning systems rely on many technologies to facilitate the localization process. Methods like Time Of Arrival (TOA) [9] and Time Difference Of Arrival (TDOA) [10] can use characteristics of wireless signals to perform both indoor and outdoor localization. Sensor data fusion from multiple sensors with different characteristics can also be used for position estimation. When the characteristics of deployed sensors are well known, variations of Kalman Filters—like the basic Kalman Filter (KF) [11], the Extended Kalman Filter (EKF) [12], and the Sigma Point Kalman Filter (SPKF)—can be utilized [13].

✉ Mohammed Elbes
m.elbes@zuj.edu.jo

Ahmad Alkhatib
ahmad.alkhatib@zuj.edu.jo

Ala Al-Fuqaha
aalfuqaha@hbku.edu.qa; ala.al-fuqaha@wmich.edu

Junaid Qadir
junaid.qadir@itu.edu.pk

1 Department of Computer Science, Alzaytoonah University of Jordan, Amman, Jordan

2 Department of Computer and Information Systems, Alzaytoonah University of Jordan, Amman, Jordan

3 Information and Computing Technology (ICT) Division, College of Science and Engineering (CSE), Hamad Bin Khalifa University, Doha, Qatar

4 Department of Computer Science, Western Michigan University, Kalamazoo, MI 49008, USA

5 Department of Electrical Engineering, Information Technology University (ITU), Lahore, Pakistan

Precise positioning systems are gaining rising popularity as Location Based Services (LBSs) are becoming part of many applications such as advertising, emergency situations, and other applications. The Global Positioning System (GPS) is able to determine the location of any localization target without any previous knowledge of its location. However, GPS location accuracy is still limited to several meters. Furthermore, GPS chip is known to be power hungry which drains device battery very rapidly. Also, The accuracy of GPS can decrease to more than 10 meters when insufficient GPS signal is received among high buildings or dense tree regions. For these reasons, several technologies and algorithms were developed in the past decade for location estimation starting from sensor data fusion to dead reckoning and simultaneous localization and mapping (SLAM).

The ready availability of location-related information from off-the-shelf devices such as RFID and Wi-Fi [14, 15] has provided a boon to the demand of such applications. In terms of RFID technology, three different types of information are available using off-the-shelf RFID technology, namely (1) signal phase information, (2) Received Signal Strength Indicator (RSSI), and (3) proximity information. Proximity-based methods exploit the ID information of tracked tags [16, 17] while localization is achieved by measuring the distance between the tag and the antennas in the phase and the RSSI-based methods [18, 19]. RSSI-based methods require absolute preliminary calibration and suffer from coarse accuracy as they are severely affected by the propagation environment, and the properties of the tagged object and cannot be represented by a universal distant-dependent path loss model [20].

In this paper, we present a novel localization approach in urban areas in which we perform fusion of data collected from multiple sensor technologies. These technologies include our Inertial Navigation System (INS), which comprises a gyroscope, a tri-axial accelerometer, and an MIT Cricket system [21] with a digital compass used for gyroscope drift calibration. This INS constantly provides the distance traveled along with its direction. Particle filters are then used to fuse the distance obtained from the INS system with the signal phase shift fingerprints collected from multiple AM radio towers.

The rest of this paper is organized as follows. We introduce the relevant background and highlighted important related works in Section 2. Section 3 explains our previous outdoor localization approach and the problems we encountered in that approach. In Section 4, we present our novel localization approach in urban areas, we describe our simulation setup and assumptions along with results obtained from simulation experiments in Section 5, and the papers conclude in Section 6.

2 Background and related work

In this section, we present a background about the localization technologies used in this paper. In particular, we provide a brief introduction to Kalman filter and its extensions and also introduce the particle filter. Thereafter, we detail the salient aspects of sensor data fusion, Chanel State Information (CSI), and fingerprinting. We discuss each technology separately and explain how we employ them together to perform localization in urban areas.

2.1 Kalman filter, extensions of Kalman filter, and particle filter

The standard Kalman filter is the optimum estimator when the state transitions can be described by a linear model and the system noise is Gaussian. When the state transitions are non-linear, they can still be linearized through appropriate approximations such as the Taylor series approximation. If the system is near-linear and has Gaussian noise, an EKF is appropriate. But these models are not appropriate for non-Gaussian distributions, which is the domain of particle filters (PFs). However, for real-life systems that do not nicely match a linear approximation, or if the sensor uncertainty is not Gaussian, a particle filter—a non-parametric filter—can be called upon to handle models with arbitrary probability distributions [22]. Particle filters (PFs) can handle and estimate any kind of a probability distribution and evidence since it attacks the problem through multiple individual "particles," which can be thought of as a possible state of the model and a sufficiently large number of particles. PFs work by using random samples (which are called particles) for the representation of the probability distribution (instead of using just the mean and covariance, which is sufficient for describing the Gaussian).

Location estimation is represented by using particles in a PF. PFs use multiple particles for state distribution estimation. The distribution of particles depicts the actual state distribution when the number of particles generated is increased. However, the computation times increases when the number of particles increases. On the other hand, KF has restrictions on system model and uncertainty features in an application. Yong et al. in [23] conducted a study comparing between both the PF and KF for robot localization. The study showed that PF and KF both provide more accurate localization compared to the methods of trilateration and triangulation. Furthermore, PF results in a robust and smoother trajectory estimation compared to KF but requires more computation time.

Localization of robots in indoor environments is a common problem in robot community. An accurate robot location estimation is required for the robot to safely navigate in indoor environments. To address this problem, Xiao et al. utilized an EKF to change the proposal distribution of the traditional distribution [24]. Additional resampling is also performed when necessary to solve the particle degeneracy problem. Furthermore, the particle divergence is controlled through the application of a Gaussian smoothing process on the sampled particles. The experiments conducted in [24] showed that the map-based PF localization with proposal distribution based on EKF is effective and avoids the disadvantages of the classical PF when the overlap of the Probability Density Functions (PDFs) of the prior and the measurements is small.

Robust and precise localization is considered a mandatory requirement for modern vehicle access systems. Recently, systems like ConfortGo and Comfort Access are considered standards in today's high-end automobiles. These systems control the user access to the vehicle by locating the key fob inside or near the vehicle. Determining the precise location of the key fob using ultra wide band (UWB) ranging is still under wide industry investigation. In [25], Knobloch discussed the challenges of using UWB ranging techniques for key fob location estimation. The authors investigated the usage of trilateration and particle filter approaches to address this problem and proposed using PF to combine the benefit of enabling non-Gaussian observation error distribution and mapping of a particle cloud to vehicle zone. The experimental results in [25] show that the performance of trilateration-based PF does not provide the required accuracy.

The fourth industrial revolution and modern factories demand solutions for monitoring the work area and supporting the assets assembly process. One of the major tasks in this context is localize and keep track of hand-driven tools, autonomous robots, and various types of vehicles. This problem was investigated in the work performed by Lipka et al. [26]. The authors proposed an approach that uses microwave-based localization system such as the 2.4 GHz modulated continuous wave radar and utilized the measurements of the Angle of Arrival (AoA) for 3D velocity and location estimation. Furthermore, the authors used the EKF to determine the transponder location from bearing measurements and to reduce measurements outliers.

2.2 Data fusion for indoor and outdoor localization

Sensor data fusion is used extensively in performing localization. The reason for this is that using data from multiple sensor technologies induces more location accuracy [27]. One of the most popular data fusion techniques is to use a Kalman Filter. This technique assumed a linear system model with additive independent white noise and is optimal estimator for such models. Since most engineering systems are non-linear rather than linear, the basic Kalman filter has been extended for non-linear systems with the development of techniques such as Extended Kalman Filter (EKF) [28] and Unscented Kalman Filter (UKF) [29], which are suitable for almost-linear systems. Techniques such as EKF adopt techniques from calculus such as the multivariate Taylor series expansion to linearize a model around a working point. These filters (EKF and UKF) however have a deficiency that they do not integrate distributed map information for object tracking. This has motivated the development and the adoption of Particle Filters (PF) [30].

Belakbir et al. [31] fused GPS with ultra wide band (UWB) sensor data to achieve outdoor localization. Several UWB sensors were placed on the top of a building while a mobile unit was moving around the building. The authors used a system called Location Information Fusion System (LIFS) to fuse the UWB and GPS sensor data. The authors of LIFS claim sub-meter location accuracy both indoor and outdoor.

In another work, Kok et al. [32] used the information about the Earth's magnetic field to construct indoor mapping. Their approach was to collect periodic measurements of the magnetic field oscillations and submit these measurements to an offline learning process. MEMS sensors such as gyroscopes, accelerometers, and magnetometers were used to obtain the location and the orientation of the mobile device. The accuracy of their fusion system started with 0.3 m and eventually decreased to about 0.2 m after 42 s as a result of the application of means to previously obtained location estimates.

Walters and co-authors in [33] fused Wi-Fi sensor data with inertial sensor measurements to construct a navigation system for the blind and visually impaired in health-related environments based on wearable devices. The idea was to associate complementary data fusion with redundant fusion to build an offline database of Wi-Fi and inertial sensor readings to be compared with test readings obtained from a mobile device. The results in [33] showed that the raw readings of RSSI and gyroscope presented high error rates. On the contrary, these rates were drastically decreased when fusing RSSI and inertial measurements to 0.38 m.

Kalman filtering was used in [34] to perform data fusion of relative sensors like robot wheel information with absolute sensor data sources like GPS and compass. This data fusion combines the advantages of relative sensors regarding their local accuracy with the ability of absolute sensors to confine the global uncertainty. The problem of the methods used in [34] is the unavoidable saw-tooth pattern, which could be mitigated by a causal smoothing with the present sensor configuration.

2.3 Channel state information

The significant capabilities of the evolving Software Defined Radio (SDR) systems permit the employment of AM radio signals in localization in urban areas. Phase shifts in signals received from locally deployed Low Power AM (LPAM) radio base stations can be used to estimate the distance between an AM radio receiver and the radio towers. Hence, the absolute position of the receiver can be estimated with a Euclidean coordinate system [35].

Channel state information is broadly used for the purposes of localization recently. The modification of the device driver in Network Interface Cards (NIC) like Intel Wi-Fi Links allows for obtaining channel state information to be used for localization purposes [36, 37]. The work in [38] combined both RSSI and phase shifts in UHF-RFID signals obtained from passive tags installed on room ceiling using unscented Kalman filter to locate localization target in indoor environments. The authors presented a two-stage algorithm to achieve indoor localization. In the first stage, only RSSI information is used to estimate the localization target's location. Phase shift information is used in the second stage using a dynamic criterion based on the variance of the location estimates of the tags. The suggested two-stage algorithm could locate localization target with one-meter accuracy.

Zhang and co-authors in [39] accomplished indoor Device-Free Localization by fingerprinting of CSI data to overcome the multipath problem existing in RSSI-based indoor localization. They presented an approach called *Ailot* that explores novel features available in CSI at the physical layer. The authors compared their maximum-likelihood based Ailot approach with the *Horus* [40] approach. Their experiments were conducted in a place divided into cells with the presence of rich multipath. The results presented an accuracy of 1.5 m and a 50 percent accuracy of 1 m.

The *PhaseFi* system proposed in [41] employs calibrated channel state information for indoor localization using fingerprinting. In the proposed system, signal raw phase information from multiple subcarriers of the 802.11n network was initially extracted from a modified NIC driver. Calibrated phase information was then obtained using linear transformation of the raw data. The authors then use a three-stage deep neural network to train the system using the calibrated data. The computational complexity of the neural network was reduced using a greedy learning algorithm to train the weights of the neural network. The experimental result in [41] shown that their proposed system outperform three benchmark schemes based on either CSI or RSS in both scenarios.

In this paper, we perform fingerprinting of phase shifts between signals obtained from locally deployed LPAM radio towers to accomplish localization in urban areas. Furthermore, we utilize particle filter for data fusion of phase shit fingerprints and our own inertial navigation system to enhance the localization accuracy.

3 Our previous localization approach

Glenn Ballou in [42] defines phase shift as any change that occurs in one signal or the difference in phase between two signals with the same frequency. In this paper, we use Φ to represent the shift in phase from zero. Phase shift between two signals is equivalent to the time delay between the two signals for infinitely long sinusoids. For instance, if the time signal Ω(t) is shifted by half of its cycle, then it will be expressed as

Ω(t - 1/2 T) = C sin (2πf (t- 1/2 T) + Φ) = A sin (2πf t - π/2 + Φ) which is equal to Ω (t) shifted by /2 radians.

In our outdoor localization approach in [35], the SDR system on the localization target assembles phase shifts in signals received from locally deployed LPAM towers. The system uses triangulation to estimate the distance between the localization target and the towers. In a setup of three towers { T_1 , T_2, T_3}, the distances between the towers and the localization target {R} are expressed by [35]

$$D_R^{T_1} = c.t_R^{T_1} \tag{1}$$

$$D_R^{T_2} = c.t_R^{T_2} \tag{2}$$

$$D_R^{T_3} = c.t_R^{T_3} \tag{3}$$

where $D_R^{T_i}$ is the distance between T_i and R, c is the Speed of Light, and $t_R^{T_i}$ is the signal propagation time from R to T_i. The SDR system on the localization target requires at least three signals to estimate each $D_R^{T_i}$ according to the following equations:

$$\frac{D_R^{T_1} - D_R^{T_2}}{c} == \Phi_{T_2}^{T_1} \tag{4}$$

$$\frac{D_R^{T_1} - D_R^{T_3}}{c} == \Phi_{T_3}^{T_1} \tag{5}$$

$$\frac{D_R^{T_2} - D_R^{T_3}}{c} == \Phi_{T_3}^{T_2} \tag{6}$$

where $\Phi_{T_j}^{T_i}$ is the observed phase shift between the signals from T_i and T_j. This is a configuration of three equations and three unknowns and is solved using Particle Swarm Optimization (PSO) [43, 44].

The localization region consists of M locally deployed LPAM towers uniformly distributed over the entire region as shown in Fig. 1. The phase shifts vector observed at the localization target's location is used to estimate the distances d_R^i between R and the LPAM towers by using

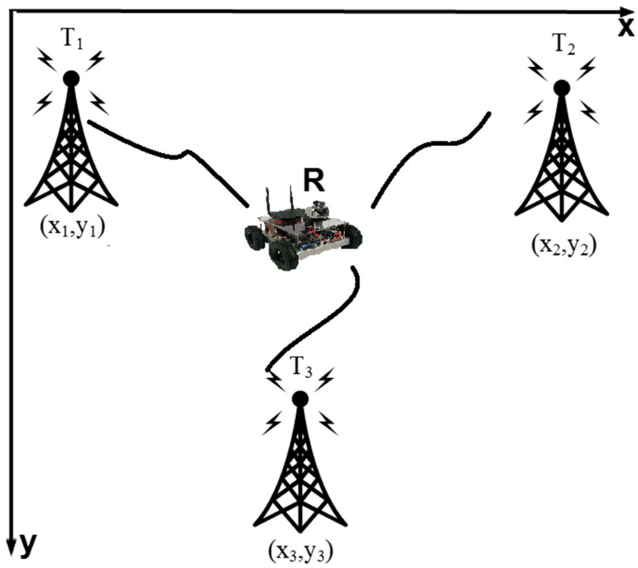

Fig. 1 Our localization coordinate system with the LPAM towers

the PSO algorithm to find a solution for the following constrained optimization problem:

Minimize:

$$\sum_{i=1}^{M}\sum_{j=i+1}^{M} |d_R^i - d_R^j - c * \Phi_{T_j}^{T_i}| \quad \forall \quad i < j \tag{7}$$

Such that

$$d_R^i - d_R^j = c * \Phi_{T_j}^{T_i} \forall \quad i < j \quad i \in \{1...M\}$$

In our outdoor localization approach in [35], we utilized the estimated M distances d_R^i between the localization target and each LPAM tower to estimate the absolute target location using the following unconstrained optimization problem:

Minimize:

$$\sum_{i=1}^{M} |d_R^i - \sqrt[2]{(X_R - X_{T_i})^2 + (Y_R - Y_{T_i})^2}| \tag{8}$$

where (X_R, Y_R) is the estimated location of the target and $(X_{T,} Y_{T_i})$ is the location of T_i.

This strategy of finding the real-time location of the localization target by continuously solving the two optimization problems in (7) and (8) presented a significant computational time for the target location estimation. The reason for this considerable computation time is that each time the target moves, the phase shifts vector observed by the SDR system on the target is sent to a processing unit that estimates the target's location using PSO, which causes delays in the location determination process.

4 Proposed localization approach in urban areas

In this section, we illustrate our proposed approach for localization in urban areas by describing our phase shift fingerprinting methodology, our inertial navigation system (INS) component design, and finally our particle filter–based data fusion technique.

4.1 Phase shift fingerprinting

In this paper, we propose an approach based on the offline collection of features called fingerprints. By definition, fingerprinting relies on collecting sufficient sensor readings beforehand in order to be matched with live readings obtained at the localization target location [45]. The location fingerprinting process is carried out in two stages [27]:

1. *Offline stage*: In this phase, a configuration of the localization region is set up such that vectors of phase shifts in signals obtained from reachable LPAM towers are surveyed at certain known locations in the localization region. These phase shift vectors along with their known coordinates are then stored as location tags in an offline database to be used later for real-time localization.
2. *Online stage*: The localization approach uses the phase shifts collected at the current localization target's location and the location tags in the fingerprint database to estimate the target's location.

In our indoor localization approach in [27], we utilized the Received Signal Strength Indicator (RSSI) obtained from nearby access points to construct the fingerprint database. These fingerprints are then fused with measurements from our own Inertial Navigation System (INS) that is based on dead reckoning for location estimation. The main challenge in this approach was that RSSI measurements vary significantly at the same location due to multipath and channel fading in signal propagation.

On the other hand, our localization technique in this paper uses channel state information such as phase shifts to perform fingerprinting. Raw phase shifts also suffer from various sources of error such as Carrier Frequency Offset (CFO) and Sampling Frequency Offset (SFO) [46]. SFO is generated by the Analogue to Digital Converter (ADC) on the receiver while CFO is due to the lack of synchronization between the receiver and transmitter clocks [47]. To overcome this problem, we adopt the phase shift sanitization technique proposed in [48] in which a linear transformation is performed to remove SFO and CFO from the calibrated phase.

Table 1 The fingerprint representation in the database

Fingerprint	Location
$FP_1 = \left\{ \begin{matrix} 1 & 1 & 1 & 1 & & 1 & & 1 \\ \Phi_{T_1}^{T_2}, & \Phi_{T_1}^{T_3} & ,\Phi_{T_1}^{T_4}, & \Phi_{T_1}^{T_4}, & \ldots, & \Phi_{T_1}^{T_N}, & \ldots, & \Phi_{T_i}^{T_j} \end{matrix} \right\}$	$L_1 = (X_1, Y_1)$
$FP_2 = \left\{ \begin{matrix} 2 & 2 & 2 & 2 & & 2 & & 2 \\ \Phi_{T_1}^{T_2}, & \Phi_{T_1}^{T_3} & ,\Phi_{T_1}^{T_4}, & \Phi_{T_1}^{T_4}, & \ldots, & \Phi_{T_1}^{T_N}, & \ldots, & \Phi_{T_i}^{T_j} \end{matrix} \right\}$	$L_2 = (X_2, Y_2)$
...	
$FP_M = \left\{ \begin{matrix} M & M & M & M & & M & & M \\ \Phi_{T_1}^{T_2}, & \Phi_{T_1}^{T_3} & ,\Phi_{T_1}^{T_4}, & \Phi_{T_1}^{T_4}, & \ldots, & \Phi_{T_1}^{T_N}, & \ldots, & \Phi_{T_i}^{T_j} \end{matrix} \right\}$	$L_M = (X_M, Y_M)$

After removing the CFO and SFO from the calibrated phase, we construct the fingerprint database. The database contains M vectors of phase shifts between signals received from the N nearby LPAM towers. Table 1 illustrates the structure of the location fingerprints database where the k^{th} row shows the phase shifts surveyed along with their corresponding location. The fingerprint FP_K is represented by:

$$FP_K = \left\{ \begin{matrix} k & k & k & k & & k & & k \\ \Phi_{T_1}^{T_2}, & \Phi_{T_1}^{T_3} & ,\Phi_{T_1}^{T_4}, & \Phi_{T_1}^{T_4}, & \ldots, & \Phi_{T_1}^{T_N}, & \ldots, & \Phi_{T_i}^{T_j} \end{matrix} \right\} \tag{9}$$

where $1 \le k \le M$, $1 \le i \le N-1$, $i < j \le N$ and $\Phi_{T_i}^{T_j}$ is the phase shift between the signals of the i^{th} and the j^{th} LPAM towers. Hence, the FP_K vector contains $V = \frac{N(N-1)}{2}$ phase shift entries collected from the various LPAM towers.

The construction of the offline phase shift fingerprint database allows for real-time localization. When the SDR system on the localization target surveys the signals phase shifts from all nearby LPAM towers, it forms the phase shift vector:

$$R = \left\{ \begin{matrix} R & R & R & R & & R & & R \\ \Phi_{T_1}^{T_2}, & \Phi_{T_1}^{T_3} & ,\Phi_{T_1}^{T_4}, & \Phi_{T_1}^{T_4}, & \ldots, & \Phi_{T_1}^{T_N}, & \ldots, & \Phi_{T_i}^{T_j} \end{matrix} \right\},$$

which represents the phase shifts in all signals from all nearby towers at the localization target's location.

The estimation of the target's location is then treated as a classification problem. Priwgharm et al. in [49] used the Euclidean Distance (EUC) technique to find the distance D_k^R between the k^{th} fingerprint and the localization target (R) using the following equation:

$$D_k^R = \sqrt{\sum \left(\overset{R}{\Phi_{T_i}^{T_j}} - \overset{K}{\Phi_{T_i}^{T_j}} \right)^2} \quad \forall \quad 1 \le i \le N-1, i < j \le N \tag{10}$$

where N is the number of access points. After finding D_k^R for each fingerprint, each fingerprint is given a weight μ_K in the location estimation process such that

$$\mu_K = \frac{1}{D_k^R} \tag{11}$$

The weights for all fingerprints are then added to find the total weight μ for all fingerprints:

$$\sum_{k=1}^{M} \mu_K \tag{12}$$

The probability that the object is near fingerprint is then given by

$$P(FP_K|R) = \frac{\mu_K}{\mu} \tag{13}$$

Based on (14), the estimated location of the localization target is calculated using the following equation:

$$L_R(X, Y) = \sum_{i=1}^{M} P(FP_i|R) L_i^{FP}(X, Y) \tag{14}$$

The following algorithm summarizes the location estimation process using phase shifts:

Algorithm 1 EUC(Φ, R).

1. *Receive the phase shift vector R from all nearby LPAM radio towers.*
2. *Compute the D_R distance from all M fingerprints in the database.*
3. *Find the weight μ_K for the k^{th} fingerprint.*
4. *Estimate the X coordi nate for the localization target's location using $X = \sum_{i=1}^{M} \mu_K * X_k$*
5. *Estimate the Y coordinate for the localization target's location using $Y = \sum_{i=1}^{M} \mu_K * Y_k$*

4.2 Our Inertial Navigation System

In earlier research [50], we presented a novel technique for performing Pedestrian Dead Reckoning (PDR) using various sensor technologies including gyroscopes, tri-axial accelerometers, and MIT Cricket system [21] for gyroscope drift calibration. In that work, we have showed how our PDR approach provides precise directional distances traveled by user and solves common sensor problems such as accelerometer bias and gyroscope drift using MIT Crickets. Furthermore, we enhanced the INS system by adding a digital compass to get more precise direction from the INS system. This system will provide the directional distance traveled by the localization target. This distance along with its direction are then fed to the particle filter to be fused with phase shifts to perform precise localization. Figure 2 shows the installation of the INS on the feet and more details about its design and implementation can be found in [50].

4.3 Data fusion using particle filter

The problem in localization based on particle filter resides in finding the joint posterior P($V_{1:t} \mid O_{1:t}, I_{1:t}$) about the trajectory $V_{1:t}$ of the localization target in the localization region where $O_{1:t}$ are the observations and $I_{1:t}$ are the measurements obtained from our INS for dead reckoning.

The use of particle filter is a common technique used for indoor and outdoor localization. Each particle is considered a pose hypothesis of the current localization target location. In this work, we implement two versions of the particle filter. In the first version, we randomly generate particles to spread all over the localization area. Each particle is then given a weight based on its distance from the phase shifts that are close to the phase shifts observed at the target's location. Particles are selected based on their weights and those particles with lower weights are then rejected. The distribution of the actual target location is mainly represented by the remaining particles. This version of the particle filter is called *Sampling Importance Resampling* particle filter and is known to keep the diversity of the particles. This process is summarized in the following steps:

1. Generation Step: a set of N particles $\{x_1(0), x_2(0), ..., x_N(0)\}$ are generated according to the initial Probability Density Function PDF $(x(0))$

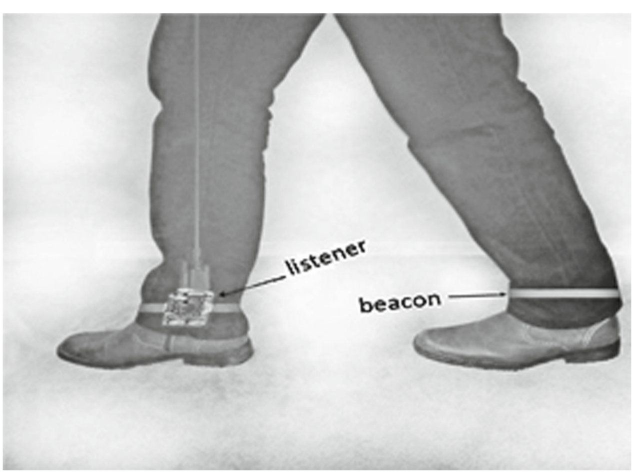

Fig. 2 Installation of Cricket beacon and listener for Pedestrian Dead Reckoning (PDR)

2. Prediction Step : Given the previous particle $P_i[x(k), y(k)]$, generate the next iteration particles according to the following equations:

$$x_i(k+1) = x_i(k) + N(\mu, \sigma) \tag{15}$$

$$y_i(k+1) = y_i(k) + N(\mu, \sigma) \tag{16}$$

3. Importance weighting : generate the particle's weight $w_i(k+1)$ for each particle $X_i(k+1)$ where $w_i(k+1)$is calculated by:

$$FP_{closest} = min(X_i(k+1), FP_k) 1 \leq k \leq M \tag{17}$$

   where N is the number of location fingerprints, and $FP_{closest}$ is the closest fingerprint to the particle $X_i(k+1)$ in the Euclidean Coordinate system. After finding the closest fingerprint to the particle $X_i(k+1)$, the phase shift distance between that fingerprint and the observed phase shifts at the localization target location $\overset{R}{\phi}{}^{T_j}_{T_i}$ according to:

$$D^R_{FPclosest} = \sqrt{\sum \left(\overset{R}{\Phi}{}^{T_j}_{T_i} - \overset{FPclosest}{\Phi}{}^{T_j}_{T_i} \right)^2} \tag{18}$$

   1≤ i≤ N-1 , i < j ≤ N , N is the number of access points. After finding $D^R_{FPclosest}$ for the $X_i(k+1)$ particle , the particle's weight $w_i(k+1)$ is then given by:

$$w_i(k+1) = \frac{1}{D^R_{FPclosest}} \tag{19}$$

4. Normalization and Resampling Step: A subset of q particles is then sampled according to their weights to circumvent the particle degeneracy. This step keeps a sufficient number of particles to approximate the actual localization target location distribution.

The dynamics of the second version of the particle filter are controlled by our INS subsystem in generating the next pose hypothesis V_t from V_{t-1} according to the equations:

$$x_i(k+1) = x_i(k) + dcos\Theta + N(\mu, \sigma) \tag{20}$$

$$y_i(k+1) = y_i(k) + dsin\Theta + N(\mu, \sigma) \tag{21}$$

where d and θ are the distance and its direction obtained from the INS after each step. Figure 3 shows the structure of our localization approach in urban areas where the calibrated distance and angle from our INS along with the phase shifts observed from the SDR system on the localization target are fed to the particle filter to perform precise localization.

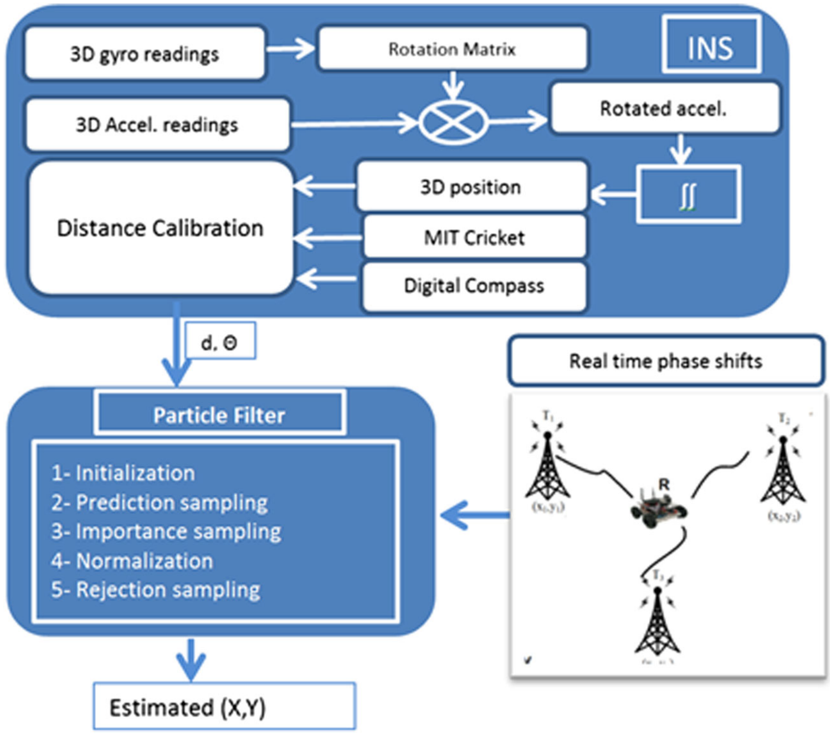

Fig. 3 Our localization techniques using PF

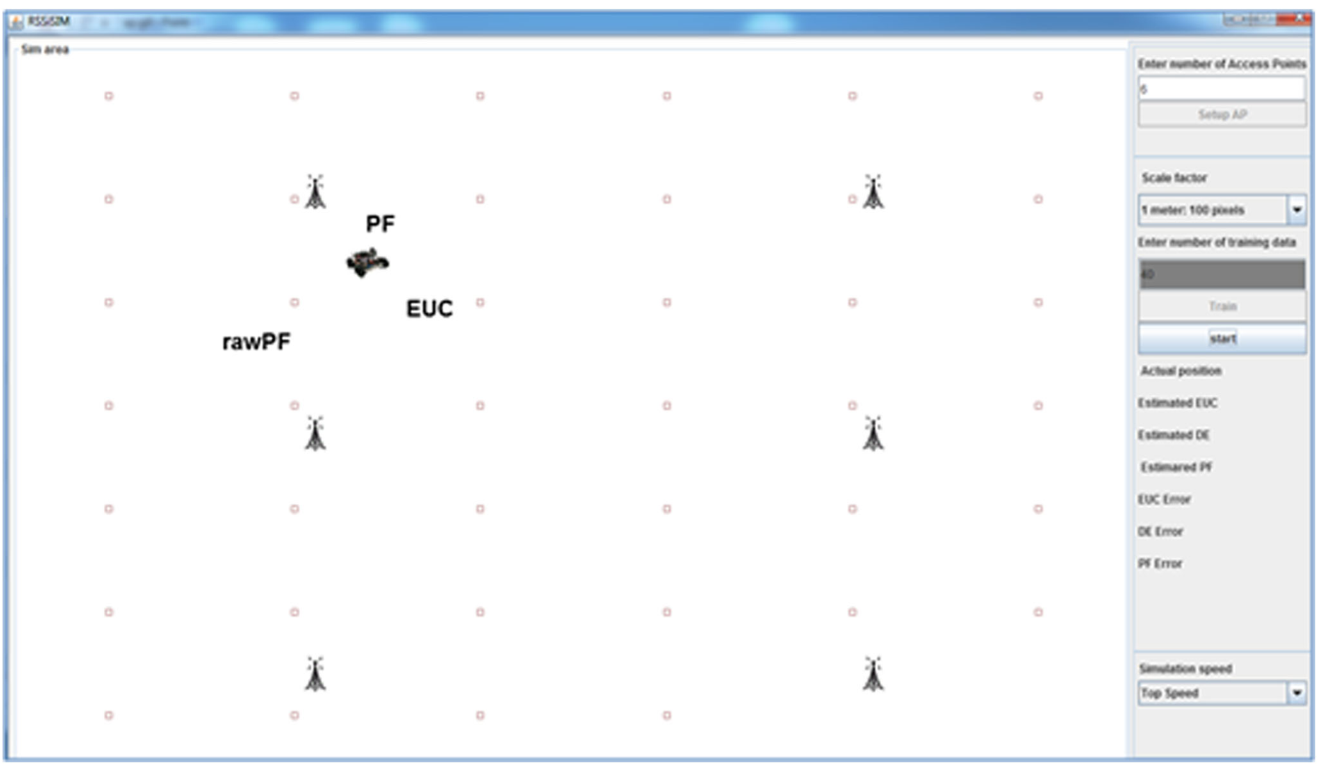

Fig. 4 Our localization simulation framework. The source code of our simulator is available on GitHub through the following URL: https://github.com/mohammedelbes/OutdoorLocalization-/

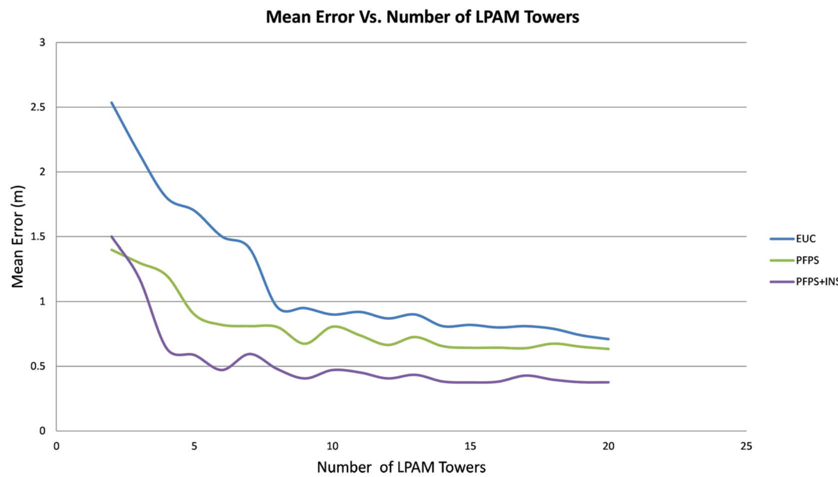

Fig. 5 Mean location error versus the number of LPAM radio towers. The figure shows that increasing the number of LPAM in the localization region greatly affects the mean location error for the three approaches. The figure shows that a limited number of LPAM can achieve a localization accuracy of about 0.3m

5 Simulation setup and results

As shown in Fig. 4 , the localization area is set up as 100 $\times$ 100 m^2. The user enters the number of LPAM towers to be uniformly distributed over the localization area. After the setting up of LPAM towers, the user enters the number of fingerprints that are also distributed uniformly over the area and their values are obtained according to (10). The LPAM towers are randomly split into noisy and non-noisy towers. The source of the noise is usually from nearby power lines or electric motors with a noise factor randomly ranging from 1 to 5 m. Our INS system is assumed to have an accuracy of about 5 cm on average.

When the simulation starts the localization target starts moving all over the area with random speeds and directions. On each simulation step, the simulator generates phase shifts at the target's location and these phase shifts are fed to the particle filter to estimate the target's location accordingly. Figure 4 illustrates a snapshot of the actual target's location along with the estimated location using EUC technique explained in Section 4.1 (EUC), the location estimated using the particle filter without INS guidance (rawPF) according to (15), (16) and the location estimated according to (20), (21), where data fusion between INS measurements and phase shifts using particle filter (PF).

To assist other researchers in replicating and extending our work, we have publicly released our algorithm and simulation source code, which can be accessed at https://github.com/mohammedelbes/OutdoorLocalization-/.

The effectiveness of the proposed localization approach has been investigated thoroughly by running several simulation experiments in different scenarios. The main goal of this localization approach is to perform data fusion from multiple technologies to achieve a minimum localization error. The data fusion of phase shift measurements and INS (PFPS+INS) data is compared with the fingerprinting technique (EUC) and with the particle filter using phase shifts only (PFPS).

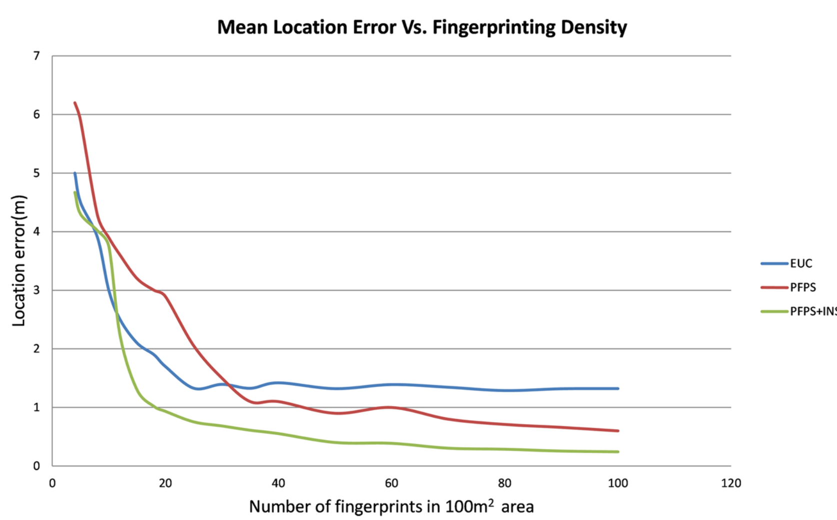

Fig. 6 Mean location error versus the number of fingerprints. The localization accuracy is directly related to the fingerprinting density in the urban area. 50 fingerprints in an area of a football field achieves an accuracy of 0.3 m

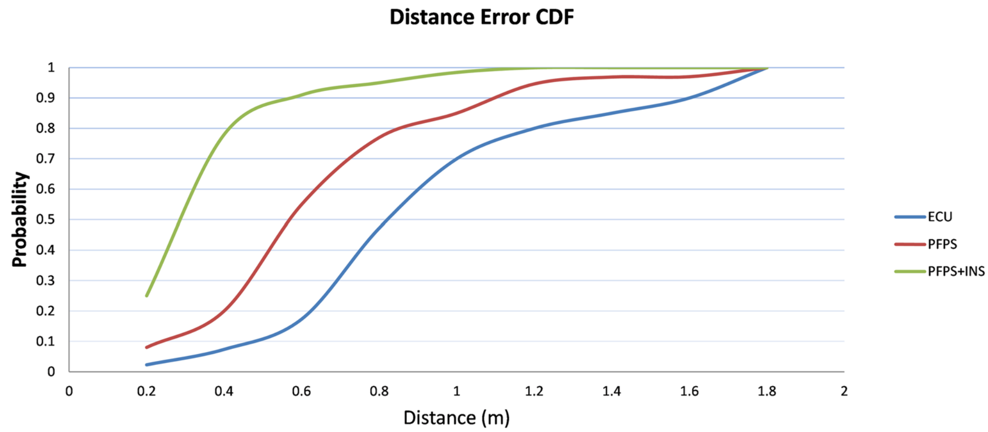

Fig. 7 Localization accuracy CDF. The figure shows that the probability that the localization target is within 0.2 m is about 25% for PF+INS and about 5% for both EUC and PFPS. This probability increases quickly to about 95% within the 0.65 m range for the PFPS+INS and is about 40% and 60% for EUC and PFPS respectively

5.1 Effect of increasing the LPAM towers density on the mean location error

The first experiment investigates the effect of increasing the density of LPAM towers on the mean location error as shown in Fig. 5. The experiment shows that increasing the number of LPAM in the localization region greatly affects the mean location error for the three approaches mentioned early in this section. Using the EUC approach, the mean error drops from about 2.5 meters when using only two LPAM towers to about 0.7 meters when having 20 LPAM radio towers in the localization region. On the other hand, using particle filter for localization reduces the mean error from 1.5 m to about 0.63 m for the same number of LPAM mentioned. The figure shows the great enhancement achieved in the mean error by using data fusion of phase shifts and INS data where the mean error drops to about 0.3 m only. The figure also shows that increasing the number of LPAM towers enhances the mean error to a certain point, after that, no enhancement is achieved. The optimal number of LPAM radio towers is shown to be 15 for the setup localization region.

5.2 Fingerprinting density required to achieve the acceptable mean location error

Based on the previous experiment which shows that the best number of LPAM radio towers is 15, this experiment uses this number of towers to study the density of fingerprinting that is required to achieve the acceptable mean location error. Figure 6 shows that increasing the number of fingerprints in the area enhance the localization precision for the three approaches. The mean location error drops from about 6.2, 5, and 4.5 m for EUC, PFPS, and PFPS+INS respectively when using only 4 fingerprints to about 1.6, 0.6, and 0.24 m when using 100 fingerprints in the localization region. The figure also shows that 50 fingerprints are enough to achieve a mean location error of about 0.3 m using particle filter for data fusion.

5.3 Cumulative Distribution Function of the location error

The Cumulative Distribution Function (CDF) of the location error shown in Fig. 7 illustrates that the PFPS+INS approach outperforms both EUC and PSPS in terms of location accuracy. Based on the previous experiments' results, a number of 15 LPAM radio towers and 40 fingerprints spread in the localization region, the probability that the localization target within 20 cm was about 25% for PF+INS and about 5% for both EUC and PFPS. This probability increases quickly to about 95% within the 65 cm range for the PFPS+INS and is about 40% and 60% for EUC and PFPS respectively.

6 Conclusion and future work

In this paper, we proposed a novel particle filter based data fusion technique. The proposed approach fuses phase shifts measurements collected from nearby Low Power AM (LPAM) radio base stations and directional distance measurements obtained from our Inertial Navigation System (INS) subsystem. Our proposed localization technique uses the advantages of high distance accuracy obtained from the MIT Cricket system and avoids its line of sight problems by installing the beacon and listener in a proper way. Our fusion technique resulted in a significant location accuracy and we are planning to further enhance the accuracy by fusing data from other sources like ultra wide band (UWB) and camera images.

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