bTracked: Highly Accurate Field Deployable Real-Time Indoor Spatial Tracking for Human Behavior Observations

Michael Chesser, Leon Chea, Hoa Van Nguyen, Damith C Ranasinghe
School of Computer Science
The University of Adelaide
Adelaide, Australia
{michael.chesser,leon.chea,hoavan.nguyen,damith.ranasinghe}@adelaide.edu.au

ABSTRACT

Methods for accurate indoor spatial tracking remains a challenge. Low cost and power efficient Bluetooth Low Energy (BLE) beacon technology's ability to run maintenance-free for many years on a single coin cell battery provides an attractive methodology to realize accurate and low cost indoor spatial tracking. However an easy to deploy and accurate methodology still remains a problem of ongoing research interest.

We propose a *field deployable* tracking system based on BLE beacon signals together with a particle filter based approach for online and real-time tracking of persons with a body-worn Bluetooth receiver to support fine grain human behavior observations.

First, we develop the concept of *generic sensor models* for generalized indoor environments and build *pluggable* sensor models for re-use in unseen environments during deployment. Second, we exploit *pose* information and *void constraints* in our problem formulation to derive additional information about the person tracked. Third, we build the infrastructure to easily setup and operate our tracking system to support end-users to remotely track ambulating persons in real-time over a web-based interface. Fourth, we assess *five* different tracking methodologies together with *two* approaches for formulating pose information and show that our method of probabilistic multilateration including the modeling of pose leads to the best performance; a mean path estimation error of 23.5 cm in a new indoor environment.

CCS CONCEPTS

• **Human-centered computing → Ubiquitous and mobile computing theory, concepts and paradigms**; **Ambient intelligence**;

KEYWORDS

Human Motion Observations, Spatial Tracking, Particle Filter, Generic Sensor Models, Bluetooth Wearable Sensors, BLE Beacons

ACM Reference Format:
Michael Chesser, Leon Chea, Hoa Van Nguyen, Damith C Ranasinghe. 2018. bTracked: Highly Accurate Field Deployable Real-Time Indoor Spatial Tracking for Human Behavior Observations. In *EAI International Conference on Mobile and Ubiquitous Systems: Computing, Networking and Services (MobiQuitous '18), November 5–7, 2018, New York, NY, USA.* ACM, New York, NY, USA, 10 pages. https://doi.org/10.1145/3286978.3287020

MobiQuitous '18, Nov. 5–7, 2018, NY, USA

ACM ISBN 978-1-4503-6093-7/18/11…$15.00
https://doi.org/10.1145/3286978.3287020

1 INTRODUCTION

Today, there is an increasing interest in accurate indoor tracking systems not just for supporting indoor navigation [6] or push advertising but also as potential tool for understanding the behavior of people, especially older people, their cognitive decline and the effectiveness of interventions to prevent such decline [18, 25, 26, 32, 34].

Although the problem of outdoor spatial tracking has largely been addressed by the Global Positioning System (GPS), accurate, easy to deploy and low cost spatial tracking in indoor environments remains a challenging problem. Consequently, in this paper we consider the problem of developing technological tools and methods to replicate the success of outdoor environments for indoor environments in the context of a field deployable system for behavior observations and understanding of older people through fine grain spatial tracking, determining accurate traversal trajectories, in smart spaces [18, 26, 32].

Although there are several wireless technologies that can be used for indoor spatial tracking, including WiFi, Bluetooth, RFID, cameras, ultrasonic range-finders, accelerometers amongst many others [1]; we aim to exploit Bluetooth Low Energy (BLE)—also known as Bluetooth Smart—as it offers many advantageous features over other wireless sensors such as: *i)* ubiquity in terms of a technology; *ii)* power efficiency; *iii)* low cost; *iv)* low form factor devices; and *v)* ability to operate for several years on a coin cell battery to provide ease of deployment while being unobtrusive to daily activities in a body-worn configuration or to the aesthetics of the environment in their deployment as beacons. Furthermore, BLE advertising channels used in beaconing occupy spaces between WiFi channels and thus signals are less susceptible collisions with WiFi channels.

Existing research has achieved, mostly, localization accuracy levels that are considered reasonable for commercial applications such as indoor navigation—see Section 7. Although commercial solutions[1] have been designed for a range of situations, they do not focus on tracking mobile targets with high accuracy and estimating trajectories but instead focus primarily on proximity detection. Further, proposed solutions yielding high accuracy are suited for

[1]for example, see:https://estimote.com/

the testing environment and are therefore not suitable for field deployments without extensive and cumbersome calibration of models such as fingerprints of signals in new environments as discussed in Section 7.

1.1 Contributions

Therefore, this paper aims to contribute to research towards realizing an easily deployable and accurate spatial tracking methodology. Our system continuously *tracks* moving targets as opposed to locating targets and therefore we solve a tracking problem as opposed to localization or positioning problem. Thus, we handle a continuous stream of beacon data collected from body-worn sensors and use a messaging bus architecture capable of handling multiple data sinks placed on the bus together with recursive Bayesian filers to perform online and real-time tracking and computation of trajectories.

In particular we make the following contributions in this work towards an accurate and real-time method to realize a field deployable BLE based spatial tracking methodology:

Exploit pose information A key challenge is to manage uncertainty created by noisy RSSI measurements of BLE beacons. We model and exploit the *pose* of the person with the wearable BLE device to improve tracking accuracy.

Formulate void constraints We recognize that movement of people are constrained by the layout of indoor spaces such as walls. Therefore we formulate *void constraints* to impose practical limitations pertinent to our tracking problem.

Propose and develop generic sensor models For a deployable system that is not specific to a particular room or environment, we require models for both the movement of targets—people in our application—and the sensors capable of being generalized over hitherto *unseen* environments. We realize that most indoor environments are similar, such as room, corridors, living rooms. Therefore we address this problem by generalizing environments into types that are commonly seen in an indoor setting. Subsequently, we create *generic* sensor models that are *pluggable* into hitherto unseen environments. This removes the to conduct *cumbersome and tedious* off-line training to develop environment specific sensor models. We demonstrate that the generic sensor models can achieve highly accurate results through evaluation of tracking accuracy in *new* unseen settings.

Experiments and Comparisons We derive, implement and compare *five* approaches for modeling raw measurements and their likelihoods for the tracking algorithm formulated with Bayesian filtering techniques to address the uncertainty imposed by measurement noise. We show that our probabilistic multilateration based tracking approach that incorporates pose estimations performs better than existing methods we compare against.

bTracked system release We have developed **bTracked**, a user friendly deployment and tracking information visualization tool to allow the rapid deployment of spatial tracking solutions in the wild as well as support the efforts of the research community—*see footnote for project data, demo video and source code released* [2].

1.2 Outline

The rest of the paper is organized as follows: Section 2 presents background work related to methods for estimating distance as well as Bayesian filters—in particular, particle filters—used in our problem formulation. In Section 3, we provide an overview of the **bTracked** system architecture and present the problem formulation in Section 4 along with key concepts we have employed to ensure generalizability of our results to unseen environments as well as ensure the practicability of our approach. Section 6 describes experiments and results. We defer related work to Section 7 and conclude our work in Section 8.

2 BACKGROUND

2.1 Distance estimation methods

The central component of BLE localization is an accurate estimation of distances from a target device and reference beacons positioned at known locations. The four most commonly used approaches include:

- **Received Signal Strength Indicator (RSSI)** involves measuring the strength of a signal at the receiving device; often reported in dBm.
- **Time of Arrival (ToA)** relies on the time required for a signal to travel from emitter to receiver to calculate the intervening distance. However, this requires that the devices be precisely time synchronized with each other.
- **Time Difference of Arrival (TDoA)** determines position by comparing the difference in time for a signal to arrive at each of the receivers.
- **Angle of Arrival (AoA)** relies on measuring direction of the signals at the receiving device and adds a layer of complexity to the receiver and antenna system due to the need for measuring the direction of arrival of a signal.

Of the methods discussed, RSSI is the most attractive option due to the relatively simple hardware requirements and the near universal capability of off-the-shelf BLE technology to measure and report RSSI values. Consequently, this paper will focus on using RSSI for estimating distances.

Although RSSI and distance are inversely correlated, RSSI values can vary considerably for different devices (even at the same distance) due to the difference in, for example, transmit power and antennas used. Even for the same device, RSSI is subject to large fluctuations due to factors such as radio signal reflections, refraction, attenuation (by obstructions) as well as orientation of transmitter and receiver [31]. Nevertheless, numerous models have been proposed to approximate the relationship [8]. The log-normal propagation is a commonly used wireless signal propagation model due to its simplistic nature. It can be applicable to both indoor and outdoor environments [11]. We describe the model below:

[2] **Demonstration video and source code:** https://github.com/AdelaideAuto-IDLab/bTracked

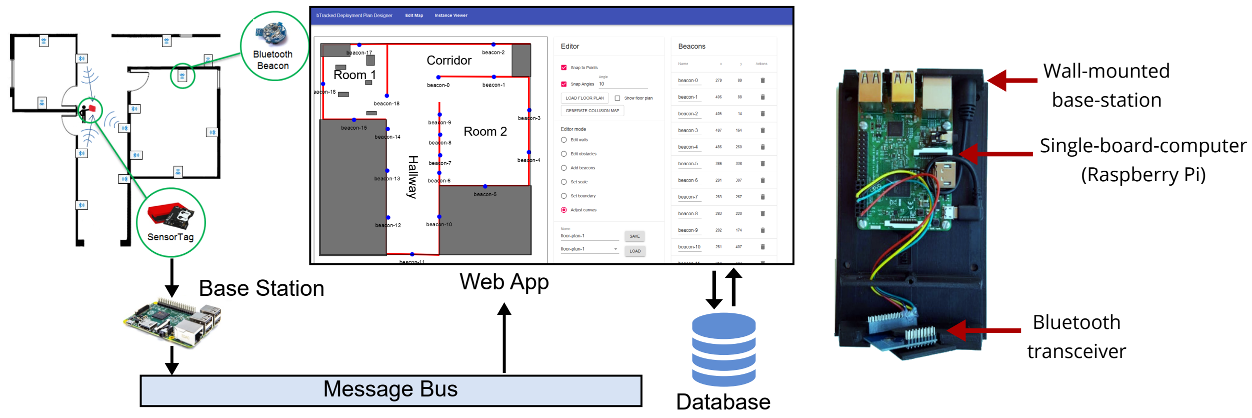


Figure 1: (left) Overview of the bTracked system, (right) a base-station (BLE transceiver and single board computer).

$$P_r(d) = P_t(d_0) - 10n \log\left(\frac{d}{d_0}\right) + X_\sigma$$

where P_r is power of the wireless signal at the receiving end, P_t is the power of the signal at the transmitting end, d is the distance between transmitter and receiver, d_0 is a reference distance usually taken to be 1 m, n is the path loss exponent—values are generally within the range of 2 to 4, depending on the environment i.e. indoors or outdoors—and X_σ is Gaussian noise (zero mean and variance σ^2) used to model the shadowing effects. More commonly, a simplified log-normal model of the form $P_r(d) = A - 10n\log(d) + X_\sigma$ where, A and n are simply parameters defined/learned for a specific environment is used.

2.2 Particle Filters

A particle filter is a Sequential Monte Carlo technique for implementing Bayesian filtering used in our problem formulation—see Section 4—to realize accurate tracking under measurement uncertainty. It works recursively, representing the posterior distribution using particles, which are updated using a measurement likelihood model together with observations—readers are referred to [2, 3] for further details while we briefly discuss the concepts below.

The Motion Model describes how the state $\boldsymbol{x}$—all the properties that define the system at a certain time—evolves over time: $\boldsymbol{x}_{t+\Delta t} = f_t(\boldsymbol{x}_t, \boldsymbol{v}_t)$ where $\boldsymbol{v}$ is independent and identically distributed (iid) process noise. Section 4 describes motion models used in our system.

The Measurement Model describes the relationship between the observation or measurement z_t and true state of the system: $\boldsymbol{z_t} = h_t(\boldsymbol{x}_t, \boldsymbol{u}_t)$ where $\boldsymbol{u}$ is iid measurement noise. We formulate and evaluate five different measurement models in our system—see Section 4.3.

Given these models, the particle filtering algorithm consists of the following four steps:

Initialization. A set of particles are drawn from a distribution representing the initial belief $p(\boldsymbol{x}_0)$, denoted by:

$$\chi_k := \{\boldsymbol{x}_{m,k}\}_{m=1}^{M} \tag{1}$$

where M is the number of particles.

Prediction. Each of the samples are propagated through the motion model $\boldsymbol{f_k}$ to represent the a priori distribution, $p(\boldsymbol{x}_k|z_{k-1})$, hence:

$$\boldsymbol{x}_{m,k} := \boldsymbol{f}_k(\boldsymbol{x}_{m,k-1}, \boldsymbol{v}_{m,k-1}) \qquad \text{for } m = 1, ..., M$$

Update. Given an observed measurement $\boldsymbol{z}_k$, the weight for each of the particles in χ_k is updated using the measurement model:

$$w_{m,k} := p(z_k|\boldsymbol{x}_{m,k}) \qquad \text{for } m = 1, ..., M$$

Resampling. After several iterations, it is possible that most of the particles have negligible weight, leaving the entire state distribution to be modelled by a few (sometimes even one) particles (particle degeneracy problem). To avoid this issue we resample the set of particles ensuring that particles with low probability are removed and replaced with other particles that may have higher weights. This is achieved through creating a new χ_k, where each sample is chosen with probability proportional to its weight.

$$\chi_k := \{\boldsymbol{x}_{n,k}|P(\boldsymbol{x}_{n,k} = \boldsymbol{x}_{m,k}) \propto w_{m,k}\} \qquad \text{for all } m, n$$

The resulting χ_k represents the a posteriori distribution $p(\boldsymbol{x}_k|z_k)$.

3 SYSTEM ARCHITECTURE

In contrast to past research, we explicitly consider the deployability aspects of the system in our design. Thus, we consider how to best allow a user to set up a tracking system starting from off-the-self beacon technologies and to allow easy viewing of the trajectories followed by the tracked person in real-time. Figure 1 presents a high level view of the individual components of the bTracked system and their interactions.

We use Texas Instruments (TI) BLE Beacons based on the CC2541 chip as the emitter of the beacon signal. They are configured to advertise 10 times per second at a transmit power of -23 dBm. Each beacon has a unique MAC (Media Access Control) address, that can allow it to be uniquely identified by the rest of the system.

The only configuration required for the beacons is the transmission power to ensure consistency in signal strengths across all beacons. Their small size and low cost allows them to be deployed very densely around a tracking area. From testing, we decide they are best placed on walls around 1.5 m from the ground, and at approximately 2 m intervals from each other.

A TI SensorTag CC2650 is used as the receiver of the BLE signals from the beacons. The SensorTag is small, can be worn around the neck with a simple lanyard and, thus, does not obstruct user activities. The SensorTag continuously scans for beacon signals, extracts the RSSI from each of these signals, and subsequently broadcasts a packet containing the detected beacon IDs along with their RSSI to a base-station—see Figure 1—which then forwards this data to a central server. Each SensorTag has a unique MAC address allowing it to be *uniquely* identified and associated with a specific user.

End-user interaction with the system is by way of a web application, bTracked Web App. The web app consists of a *Deployment Plan Designer Tool* illustrated in Figure 1 that allows the user to reconstruct the environment in which the tracking system is to be deployed. The user must enter wall and positions and IDs of the beacons used in to the system (typically by tracing a floor plan), and optionally the location and sizes of any immovable obstacles within the environment. This is linked to a database that stores different maps. We define a map as being the state space or the tracking environment, consisting of rooms, walls, beacons and obstacles. The second part of the web app is the *Real Time Trajectory Visualization Tool*, which shows the movement of the person in real time. Upon receipt of a new RSSI packet, the server executes the tracking algorithm, and then renders the display with the updated position of the person.

4 PROBLEM FORMULATION

Our primary aim is to be able to actively track a moving target—a person wearing a SensorTag in our application context—within a given map. It is assumed that the system has knowledge of this map and the state space. This is achieved by defining the area that we are interested in using the Deployment Plan Designer Tool and overlaying this with an xy plane and coordinate system.

The state of the target (a person in our problem) of interest is $\boldsymbol{x} = [x, s]^T \in \mathbb{R}^4 \times \mathbb{S}$ comprises of its kinematic state, position and velocity, $x = [p_x, \dot{p}_x, p_y, \dot{p}_y]^T$ in the xy plane, and its dynamic mode $s \in \mathbb{S} \subset \mathbb{N}$ (a natural number). The dynamics of a mobile target can be modeled by the jump Markov system (JMS) whose evolution follows a Markov chain [4]. We assume that the target motion s follows one of two dynamics models: i) the constant velocity (CV) motion model, ii) the stationary motion model as described below.

The Constant Velocity (CV) Motion Model. The model assumes that a target is moving with constant velocity and applies to a person moving around an environment. For the CV motion model, we use standard kinematic equations with zero acceleration. For a given epoch with duration Δ_t, we update the state given by:

$$x_k = A^{CV} x_{k-1} + q^{CV}, \tag{2}$$

where $A^{CV} = \begin{pmatrix} 1 & \Delta_t \\ 0 & 1 \end{pmatrix} \otimes I_2$, $\otimes$ denotes for the Kronecker tensor product operator between two vectors, and $q^{CV} \sim N(0, Q^{CV})$ is a 4×1 matrix representing zero mean Gaussian process noise, with covariance
$Q^{CV} = \sigma_{CV}^2 \begin{pmatrix} \Delta_t^3/3 & \Delta_t^2/2 \\ \Delta_t^2/2 & \Delta_t \end{pmatrix} \otimes I_2$, where σ_{CV} is the standard deviation of the process noise parameter. Notably, it is unrealistic to assume a person moves strictly at constant velocity, therefore, we add dynamic noise q^{CV} and assume this noise is based on a nearly-constant-velocity model successfully used in [10] and [16].

The Stationary (Stat) Motion Model. This model applies for all cases where a person is in a stationary position over a period of time, either standing or sitting at a particular location. In this state, the position does not change and the velocity in both directions is zero. Thus, we can expressed this model as:

$$x_k = x_{k-1} + q^{Stat} \tag{3}$$

where $q^{Stat} \sim N(0, Q^{Stat})$ is a 4×1 matrix with zero mean Gaussian process noise with covariance
$Q^{Stat} = \sigma_{Stat}^2 \Delta_t^2 [1\ 0\ 1\ 0]^T$, where σ_{Stat} is the standard deviation of process noise, Δ_t is the measurement time interval, and I_n is the $n \times n$ identity matrix. Notably, for the stationary motion model, the process noise σ_{Stat} should be zero. However, we set σ_{Stat} to be a small value instead of zero to avoid the particle degeneracy problem [7].

Now, the motion model s_k at time $(k-1, k]$ is modeled as the 2-state first-order Markov chain using a known transition probability matrix π, given by:

$$\pi_{ij}^s := P(s_k = j | s_{k-1} = i), \forall i, j \in \mathbb{S}, \tag{4}$$

such that $\pi_{ij}^s \geq 0, \sum_j \pi_{ij}^s = 1$.

4.1 Managing Variations in Pose

We conducted an experiment where we measured the RSSI when the person is in different orientations with respect to the beacon; and we observed significant differences in RSSI despite the person being at the same position. Therefore, it is important to consider the sensor orientation when using RSSI as a measure of distance.

The simplest approach is to place the beacons on the ceiling, and have SensorTag attached perhaps over the shoulder of the person or on the head. However, this is not user-friendly in practice. Consequently, we resort to the solution of monitoring the pose of the person as well as their position. We define *pose* as being the orientation of the person or the direction in which they are currently facing such that the SensorTag is oriented in the same direction. We consider two methods to achieve this:

4.1.1 Measurement of pose. The first method deals with a measurement approach for pose. We train a classifier that takes RSSI reading $\mathbf{R} = \{r_1, r_2, ..., r_M\}$ for M beacons as input, and outputs a class label specifying a direction or pose. To train this classifier, we use the fingerprints from Section 5.1 projected on to a given map. For each possible (p_x, p_y, θ) in the map, we select an RSSI reading from the RSSI distribution collected during scene analysis for each of the beacons. These are used to train the classifier; thus obtaining a function P that maps $\mathbf{R}$ to a pose θ.

4.1.2 Estimating Pose. The second method is to incorporate pose as an additional state variable to be estimated. This requires a slight alteration of the motion model as the pose also needs to be propagated with time along with the original state variables. Let $\theta \in \Theta = \{0, 1, 2, 3\}$ denote the pose of the target. Here, for simplicity, we discretized the pose into 4 possible directions with respect to the beacon (see Figure 2): *Towards, Leftwards, Rightwards, and Away-from*, which corresponds to $\theta = 0, 1, 2, 3$, in order.

Pose Transition Probability. The motion model θ_k from time $k-1$ to time k is modeled as the 4-state first-order Markov chain using a known transition probability matrix π^θ, given by:

$$\pi_{ij}^\theta := P(\theta_k = j | \theta_{k-1} = i), \forall i, j \in \Theta, \tag{5}$$

such that $\pi_{ij}^\theta \geq 0, \sum_j \pi_{ij}^\theta = 1$.

4.2 Void Constraints

Particle filters allow us to easily incorporate additional knowledge into the system. In an indoor setting, there are likely to be furniture or obstacles all around an environment. We consider the following constraints: i) it is impossible to cross any walls; and ii) it is impossible to occupy the same space as an obstacle. We ensure that our motion model abides by these void constraints.

4.3 Measurement Likelihoods

The main challenge in developing a tracking algorithm is the derivation of accurate measurement and noise models to update our state. In a particle filter, we need to compute the observation or measurement likelihood, $p(z_k|\boldsymbol{x}_{m,k})$, for each particle m, and then assign weights based on this likelihood. This likelihood describes the probability of receiving an RSSI measurement $\mathbf{R} = \{r_1, r_2, ..., r_b\}$ from the set of beacons $\mathbf{B}$, where r_b is the RSSI measurement from beacon $b \in \mathbf{B}$, given state $\boldsymbol{x}$. We discuss the five methods we consider in computing this likelihood below. Prior to proceeding further, it is important to note that, although we use sensor models developed through scene analysis, we provide a method to generalize these over a wide set of unseen environments as described in Section 5:

- The RSSI-Distance model is described in Section 5.2.
- The fingerprint models are described in Section 5.1.

Simple Trilateration. This is one of the simplest methods in the literature [9, 23, 29], and we use this method as a baseline. An RSSI-distance model is used to convert all RSSI readings to distances, then trilateration is used to evaluate a location $\boldsymbol{l} = (x, y)$ on the floor plan. We assume a Gaussian distribution with mean as

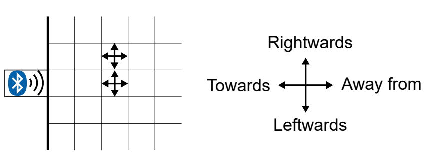


Figure 2: An overview of the method used to collect measurements for creating the generic fingerprint models. For each $25\ cm \times 25\ cm$ **interval we capture sensor data for 4 different orientations.**

the estimated location and standard deviation based on the RSSI-Distance model and the average distance to each beacon. Thus, the likelihood is given by:

$$p(\boldsymbol{l}|\boldsymbol{x}_{m,k}) \sim N\Big(||\boldsymbol{l} - \boldsymbol{x}_{m,k}|| - d_{m,b}, \sigma(\underset{b\in\mathbf{B}}{\text{mean}}\, d_{m,b})\Big)$$

where $||\cdot||$ denotes the norm operator, $d_{m,b}$ is the distance between the beacon b and the particle m, and $\sigma(d_{m,b})$ is the standard deviation obtained from the RSSI-Distance model—see Equation 7.

Probabilistic Multilateration. This method is similar to the one above except that we now assume a probability distribution based on the log-normal model [5][24]. Thus, the likelihood of an RSSI reading, r, from beacon b can be described by:

$$p(r_b|d_{m,b}) \sim N\Big(r_b - \mu(d_{m,b}), \sigma(d_{m,b})\Big)$$

where $\mu(d_{m,b})$ is the mean RSSI obtained using the log-normal model and $\sigma(d_{m,b})$ is the standard deviation—see Equations 6 and 7, respectively. Then, assuming the independence of individual RSSI measurements, the likelihood is given by:

$$p(\mathbf{R}|\boldsymbol{x}_{m,k}) = \prod_{b\in\mathbf{B}} p(r_b|d_{m,b})$$

Kullback-Leibler Divergence. Unlike the previous methods that are model-based, the Kullback-Leibler (KL) divergence method is based on RSSI fingerprints obtained through extensive scene analysis. This approach has been used by [19, 26]. A common downside of such approaches is that they are specific to an environment, however we discuss how we can utilize this approach for an an unseen environment using our generic sensor models.

In general, KL divergence is a method that can be used to compute the difference between two probability distributions. For two discrete probability distributions P and Q, the KL divergence is defined as:

$$D_{KL}(P||Q) = \sum_i P(i) \ln\left(\frac{P(i)}{Q(i)}\right)$$

where $D_{KL}(P||Q)$ is the information lost when Q is used to approximate P. In our case, where $\mathbf{R} = \{r_1, r_2, ..., r_{|\mathbf{B}|}\}$, is a set of RSSI readings from $|\mathbf{B}|$ beacons. Therefore, for our problem, we evaluate KL divergence between the measurement and the stored fingerprints F constructed for a given map (floor plan):

$$D_{KL}\Big(p(\mathbf{R}|\boldsymbol{x}_F)||p(\mathbf{R}|\boldsymbol{x})\Big) = \sum_{i=1}^{|\mathbf{B}|} p(r_i|\boldsymbol{x}_F) \ln\left(\frac{p(r_i|\boldsymbol{x}_F)}{p(r_i|\boldsymbol{x})}\right)$$

where $p(\mathbf{R}|\boldsymbol{x})$ is probability of observing RSSI reading $\mathbf{R}$ given state $\boldsymbol{x}$, and $p(\mathbf{R}|\boldsymbol{x}_F)$ is probability of observing $\mathbf{R}$ corresponding to state $\boldsymbol{x}$ in the stored fingerprints F for a given map (floor plan).

We introduce a kernel function through the exponentiation of the above KL divergence and this allows the computation of likelihood, thus

$$p(\mathbf{R}|\boldsymbol{x}) = e^{-D_{KL}\left(p(\mathbf{R}|\boldsymbol{x})||p(\mathbf{R}|\boldsymbol{x}_F)\right)}$$

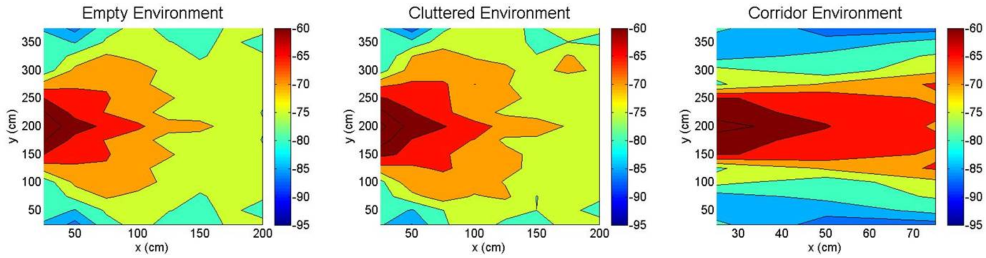


Figure 3: Generic models for different environment types for a *Towards* pose shown in Figure 2. The beacon is at (0,200).

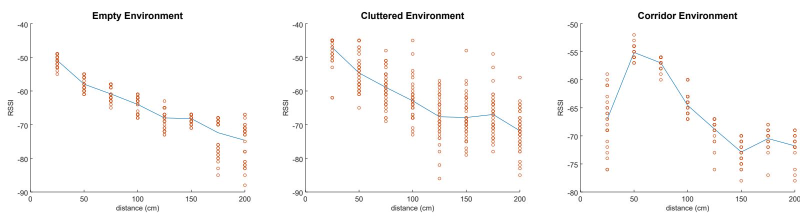


Figure 4: RSSI distribution as as a function of distance for each environment type. The corridor environment shows significant multipath affects compared to the other environments.

Classification. In this approach, a classifier is used to determine the state based on a predicted position vector $\boldsymbol{l} = (x, y)$. We consider this approach since past studies, as stated in [15], have used this method. Though any classifier can be utilized, we focus on using k-Nearest Neighbor (kNN) classifier as it is both an elegant model to the problem and simple to realize. In this approach, we take the received RSSI reading $\mathbf{R}$ and use the model built with kNN to classify it to a location $\boldsymbol{l}_f$ stored in the fingerprints F. After determining a location $\boldsymbol{l}_f$, the likelihood is then computed as

$$p(\boldsymbol{l}_f|\boldsymbol{x}_{m,k}) \sim N\Big(||\boldsymbol{l}_f - \boldsymbol{x}_{m,k}|| - d_{m,b}, \sigma(\operatorname*{mean}_{b\in\mathbf{B}} d_{m,b})\Big)$$

Probabilistic Classification. This method is a novel extension of the previous classification approach. Some, classification algorithms can be employed to generate a confidence for predicted class labels. In kNN, for example, this depends on the proximity to the predicted class, and to those of the neighboring but not predicted classes.

In contrast to the classification method, we use the prediction confidence for each class to assign likelihoods. In our case, RSSI readings $\mathbf{R}$ as input data can produce a confidence for a class label $\boldsymbol{l}_f$. We can then define a likelihood based on class confidence values as $p(\mathbf{R}|\boldsymbol{x}_{m,k}) = \text{confidence}(\boldsymbol{l}_f)$. In the case where a particle $\boldsymbol{x}_{m,k}$ does not lie on a fingerprinted location $\boldsymbol{l}_f$, we find the closest $\boldsymbol{l}_f$ based on Euclidean distance.

5 ADDRESSING DEPLOYABILITY

One of the major contributions of our work is our advancements of the system towards deployability. To accomplish this, we rely on generalized sensor models, which we develop offline, and can be easily adopted to fit into new unseen environments with minimal effort. To ensure our models from scene analysis are generic and cover all cases of common rooms types in an indoor house setting, we divide the rooms into three main categories:

Empty Room A room of arbitrary size that is primarily comprised of empty space.

Cluttered Room A room of arbitrary size where there is 'clutter' in the form of furniture.

Corridor A narrow room or walkway of width roughly around 100 to 200 cm.

Given the similarities in the architecture of typical houses—such as bed rooms, lounge rooms, hallways—in this study, we assume that all rooms will fall into one of the above categories.

5.1 Generic Fingerprint Models

We develop generic models that enable us to automatically generate RSSI distributions for a custom map. To accomplish this, we first undertake a scene analysis study to collect fingerprint data for a beacon that is placed in each of the above environments. We consider RSSI up to 200 cm away from the beacon. We record RSSI readings from the beacon at 25 cm intervals to create a map of the RSSI around the beacon. We conduct this experiment for each of the four directions shown in Figure 2: i) facing towards beacon; ii) facing away from beacon; iii) leftwards from beacon; and iv) rightwards from beacon.

We use a 2D kernel density estimation (KDE) function to create a generic model from these RSSI readings. The KDE is defined as:

$$\hat{f}_h(\{x,y\}) = \frac{1}{n}\sum_{i=1}^{n}\frac{1}{h_x h_y}K\Big(\frac{x-x_i}{h_x}, \frac{y-y_i}{h_y}\Big)$$

where n is the number of RSSI readings, K is a kernel function based on the mean RSSI readings and h_x and h_y are bandwidths based on the standard deviation of these readings. The generated RSSI maps are shown in Figure 3.

Hence, when presented with a new environment, we can generate customized sensor models for that environment automatically by simply overlaying the RSSI distribution of each deployed beacon onto the map.

5.2 Generic RSSI-Distance Models

We also develop multiple parameterised RSSI-distance models for each of the different environment types. This allows us to dynamically select the correct model to use depending on our current environment. To estimate the parameters of these models, we record RSSI measurements at regular distances from a beacon up to a distance of 200 cm. We collect multiple readings at each point to record the distribution of RSSI values at each point. Figure 4 shows a plot of this distribution along with the mean for each of the environment types. We can represent the mean (6) and standard deviation (7) of RSSI as:

$$\mu(d) = A - 10n \log(d) \tag{6}$$

$$\sigma(d) = ld + c \tag{7}$$

where d is distance from transmitter to the receiver. In deriving the model for the standard deviation (7) of RSSI, we assume that noise $\sigma(d)$ increases linearly with distance—see Figure 4. Thus, we estimate the parameters A, n, l and c for each of our environment types using a least squares fit and the results are given in Table 1. In our implementation, each beacon is associated with a different RSSI-distance model based on its surrounding environment and we select the RSSI-distance model based on Table 1.

Table 1: Estimated parameters for RSSI-distance models.

Room type	A	n	l	c
Empty Room	-14.52	2.54	0.77	0.02
Cluttered Room	-9.77	2.66	4.59	0.01
Corridor Room	-41.58	1.24	2.91	0.01

Generic RSSI-Distance Models with Pose: As mentioned in the section 4.1, pose contributes significantly to the RSSI measurements. Given the estimated pose θ relative the the beacon b (see section 4.1.2) of a target at location (p_x, p_y) in the xy-plane, the mean and standard deviation of RSSI measurements can be modeled as:

$$\mu(d, \theta, p_x, p_y) = A - 10n \log(d) + G^b(\theta, p_x, p_y), \tag{8}$$

$$\sigma(d) = ld + c. \tag{9}$$

Here, $G^b(\theta, p_x, p_y)$ denotes the normalized RSSI gain based on the relative pose θ from the target at location (p_x, p_y) to the beacon b. In this work, we use the fingerprint RSSI readings (as illustrated in Figure 3) to calculate the normalized RSSI gain $G^b(\theta, p_x, p_y)$.

6 EXPERIMENTS AND RESULTS

6.1 Settings

We conduct our field experiment within an indoor housing environment with multiple rooms that is intended to reflect how the system is expected to be used to create a smart space cable of spatially tracking its residents. Our testing environment is a house with an area of 7.5 m × 9.0 m (67.5 m^2), with four rooms: one empty room (room 2), one cluttered room (room 1), one narrow corridor and a large empty hallway that interconnects the other three. Figure 1 illustrates the map generated using the **bTracked Web App** based on the floorplan as well as the position of the 21 beacons distributed at approximately 200 cm intervals, across the map, and 150 cm above ground level. The test path trajectory that makes use of all four rooms and consequently, all of our generic sensor models is shown in Figure 5. In addition, the figure shows obstacles and areas where the person is not allowed to be in or cannot enter or are not part of an area being monitored—these areas are represented by the gray areas—and reflect the real environment under consideration. To verify the accuracy of our system in a *new* unseen deployment environment, ***none*** of the rooms used in this test environment were used for model building.

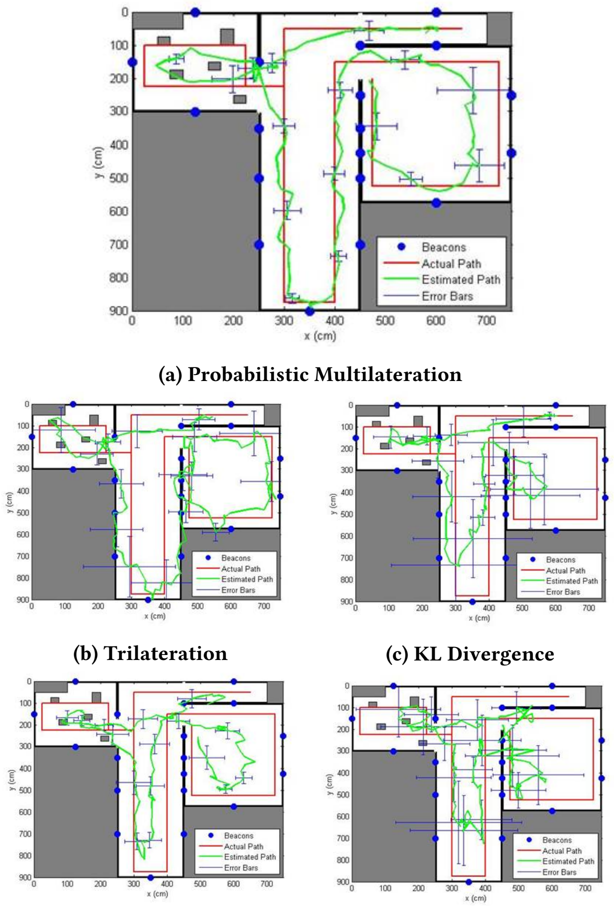
Table 2: Comparison of mean errors for the five likelihoods.

	Mean Path Estimation Error (cm)		
	No Pose	Pose in $\boldsymbol{R}$	Pose in $\boldsymbol{x}$
(a) Prob. Multilateration	38.9	33.9	**23.5**
(b) Trilateration	85.5	77.2	**51.9**
(c) KL Divergence	63.9	**61.3**	115.7
(d) Classification	63.9	61.3	**49.9**
(e) Prob. Classification	116.5	106.6	**72.2**

To record ground truth data to allow us to assess our estimations, we created a discretized path by taking 20 reference points regularly distributed across the path, and then, recorded the time it takes to move from one point to another. Assuming the person walks at constant speed throughout, we interpolated the position and time in between the reference points. The error at each estimated position is considered as the distance between the actual position and the estimated position, and the overall error of the estimated path is considered as the mean of these errors. Because of the generally noisy nature of the received RSSI, we repeat this experiment five times using each of our approaches developed in Section 4. Consequently, we present the mean error of each approach averaged over five runs in Table 2. The best method for including pose is highlighted in bold for each of the 5 methods. Figure 5 shows the estimated path trajectory for these five methods—see the green line—for a single run where the error bars show the 95% confidence interval.

6.2 Results

The results show that probabilistic multilateration achieves the best estimated path trajectory in all cases. Although multilateration is often identified as being inferior to fingerprinting techniques, this is not the case in our work. There are two potential explanations. *First*, our fingerprinting techniques are based on generic sensor models built in spaces different from those used in testing, therefore it is likely that the fingerprints are not completely accurate in describing the unseen environment compared to if the calibration was conducted in the testing room as with past work reporting higher accuracy over multilateration. *Second*, our use of a mode filter along with the retention of only beacon measurements producing the strongest RSSI readings and using these beacon data as the basis for multilateration results in more accurate estimations of



(a) Probabilistic Multilateration

(b) Trilateration

(c) KL Divergence

(d) Classification

(e) Prob. Classification

Figure 5: Path trajectories for different approaches (the starting position is at the top right corner of the map)

distances. Notably, the standard deviation in RSSI measurements is much lower when the beacons are closer—i.e. for strong RSSI readings—and we can observe this in Figure 4 and therefore relying on the strongest RSSI data from a set of measurements leads to less measurement uncertainty.

Introducing pose into the measurements produces slightly better results than without, in all cases. However, the improvement obtained is very minimal because of the large uncertainty associated with our pose measurement method based only on RSSI data. Incorporating pose as part of the estimated state leads to considerably better performance in all methods except for KL divergence. When pose is estimated as part of the state, we are not only able to better model measurement uncertainty but also system dynamics—motion of a person that includes turns, see (5).

The probabilistic classification method does not perform better than the the standard classification method in all cases. The probabilistic classification method relies on the confidence of each predicted label; thus, the performance of this approach depends on how well the classifier produces a confidence distribution reflective of the likelihood of the measurement. Overall, our results indicate that probabilistic multilateration that also models *pose* outperforms all other methods.

7 RELATED WORK

The field of spatial tracking with Bluetooth is certainly not new. One of the earlier works in this field is by Feldmann et al. [9], where the authors tried to conceptualize a positioning system with Bluetooth for indoor situations. The study used 3 access points at known random locations as beacons, and a person holding a Personal Digital Assistant (PDA) as the receiver. A log-normal propagation model determined distances from Received Signal Strength Indicator (RSSI) readings and trilateration based on least squares estimation provided position estimates. Wang et al. [30] considered an almost identical problem, using a log-normal model, and three positioning techniques (variations of trilateration); namely least square estimation (LSE), three-border positioning and centroid positioning methods.

Another similar work by Raghavan et al. [23] tracked a robot undertaking a random walk. Instead of standard trilateration, they used a variation of this known as iterative trilateration. The study achieved a mean error of 0.78 m for a furnished room but used long measurement times—a stationary robot—to collect large amount of RSSI readings for the same position and thus making their system more of a localization system than a tracking solution.

Another branch of prior work in the field of BLE tracking involves the use of fingerprinting or *scene analysis* techniques. This technique is based on careful prior characterization and storage of RSSI values at all locations within the environment; these can then be used as a reference when executing the positioning algorithm. Fingerprinting has been shown to be a more accurate technique at positioning a target [17]. However, this comes at the expense of lower efficiency due to higher memory usage and training time through the cumbersome collection of data. Nevertheless, this approach has been used by, for example, Pei et al. [21] and Iglesias et al. [12] with promising results.

Subhan et al. [28] created a hybrid approach that combined fingerprinting with trilateration to compute the final position. The highest accuracy they achieved was 2.67 m; relatively lower than those reported in other works. A unique approach is explored by Priyantha et al. [20], the authors used the Min-Max algorithm for localization. Distances obtained from a log-normal model produced a rectangle around the area the device is likely to be in, and the device then localizes itself within this rectangle through a stigmergic process. They used 8 beacons in a 6 m × 6 m room, and achieved an error of 1.8 m. Recent work has applied Bayesian filtering techniques. For instance, the study by Martella et al. [18] investigated the behaviors of museum visitors by positioning BLE beacons at the exhibits. Their systems utilize particle filters to estimate the exhibits each visitor observes and the order in which the exhibits are visited.

Summary. Table 3 presents a summary of related works, including studies using wireless network signals. We can see most accurate methods use scene analysis techniques such as finger printing and most studies are focused on localization.

Table 3: Summary of studies using RSSI from BLE beacons for localization and/or tracking with reported accuracy.

Related Work	Setting & Environment	Techniques	Root mean square error (m)
Feldmann et al. [9] 2003	Area: 8 m × 6 m empty room. 3 beacons (Implemented on a PDA based receiver).	Log-normal model propagation model. Trilateration with least squares estimation (LSE).	2.08 (localization of static objects)
Klepal & Beauregard [13] 2008	Area: 50 m × 50 m floor area. WiFi access points.	Back tracking particle filter in conjunction with fingerprinting method (used wireless LAN fingerprints instead of BLE beacons).	1.34 (WiFi)
Raghavan et al. [23] 2010	Area: 6 m × 8 m partly furnished room. 3 beacons (USB dongles).	Log-normal propagation model. Mobile robot receiver performing random motion, stop and perform 5 queries to iteratively improve location accuracy through iterative trilateration.	0.427 (localization of static observers)
Mirowski et al. [19] 2011	Area: 40 m × 40 m cluttered office. WiFi access points.	Fingerprinting method in conjunction with KL divergence.	1.16 (WiFi)
Subhan et al. [28] 2011	Area: 10 m × 12 m room. 3 beacons (USB dongles). Nokia 5130 mobile as a receiver.	Fingerprinting method with KNN. Trilateration using distances obtained from log-normal propagation model.	2.67
Zhu et al. [33] 2014	Unknown testing environment. CC2540 development boards with integrated BLE reference nodes to receive signals.	Log-normal propagation model. Use weighted windows to reduce signal fluctuations with offline trained models for online localizations. Positioning solved with least squares estimation.	1.5 (localization)
Priyantha et al. [22] 2015	6 m × 6 m office with obstacles. 8 beacons in combination with ultrasound emitters.	Log-normal propagation model. Min-Max algorithm	1.8 (localization of observer)
Kriz et al. [14] 2016	Area: 52 m× 43 m floor with multiple rooms. 4 WiFi emitters and 17 beacons. Mobile phones as receivers	Fingerprinting method in conjunction with KNN.	0.77 (localization of static objects)
Li et al. [15] 2016	Area: 20 m × 15 m floor area with one hallway and 5 rooms. 8 WiFi emitters.	Fingerprinting method using KNN. Particle filter with likelihood assuming Normal distribution around measured position.	1.3 (WiFi)
Subedi et al. [27] 2016	Area: Corridor environment of width 2.5 m. 14 beacons.	RSSI filtering using moving average filter and Kalman filter. Weighted centroid localization.	1.58
Martella et al. [18] 2016	100 m × 25 m with 60 exhibits. BLE beacons at each exhibit. 60 beacons. Receiving device worn around the neck.	Particle filter. Density-based filter. Majority-vote filter.	face-to-face proximity only
Chandel et al. [6] 2017	Area: 4 beacons with usable RSSI at each grid for a receiver where line of sight BLE beacons distances are around 8 m	BLE beacons for localization and IMU sensors embedded in the phone to track users using a particle filter.	0.9 (BLE localization, IMU sensors for tracking)
Ours	Area: 7.5 × 9 m. Corridor, hallway, one rooms with open spaces, one cluttered room. 21 beacons.	RSSI and *pose information* with *void constraints*, particle filter with probabilistic multilateration.	0.235

Our probabilistic multilateration based tracking approach performs better than other methods we have implemented and compared with. More significantly, our approach to incorporate pose estimation and void constraints outperforms methods without pose estimation; the probabilistic multilateration with pose outperforming all other methods. Further, our focus on developing a method for obtaining accurate real-time tracking of a mobile target stands in contrast to existing BLE based studies that perform localization and/or consider only static objects. Our proposed approach to build generic sensor models removes the need for labour intensive scene analysis. In addition to methodological advancements over existing studies, our performance evaluation study is conducted in an unseen environment and we release a complete system implementation to the research community.

8 DISCUSSION AND CONCLUSION

Overall, we have successfully designed a framework for a deployable online real-time indoor spatial tracking system capable of fine grain spatial tracking for human behavior observation applications. We also demonstrated system in a complex indoor environment, a target application scenario for the technology. In particular:

- We demonstrate that it is feasible to create ***generic pluggable*** sensor models that can be successfully used in unseen environments without further scene analysis; this potentially opens a range of possibilities as future works can consider the removal of the need for a labor intensive scene analysis phase for unseen environments.
- We have focused on deployability, therefore we have evaluated our approach in an ***unseen*** environment with no scene analysis, this is contrast to previous studies that mainly focused on improving only accuracy.
- We have demonstrated that modeling **pose** using the the ***two*** proposed approaches significantly improves estimation accuracy using ***five*** different measurement models; here probabilistic multilateration with pose achieves the best results.
- Although it is difficult to compare with previous studies directly because of, for example, different mobility settings, environmental settings, beacon types and deployments, we obtained a mean error of approximately 23 cm in a *new* unseen environment of 7.5 m × 9 m in a real-time tracking experiment in the wild using our probabilistic multilateration compared to other four methods we considered.
- We release our system implementation and tracking algorithms to support researchers in the field.
- Although our system is designed specifically for tracking people in an indoor environment, the entire concept can be applied just as well to objects or other environments.

Despite our successful development of a field deployable system for tracking, our approach is not without limitations and room for improvement. The greatest determinant of accuracy are the generic sensor models. We have devised three environments which we feel cover a range of possible cases in an indoor house setting. However, it would be better to decompose and add to these three categories to increase the granularity of the environment types we have considered.

Another key determinant of accuracy is how we monitor and track the pose of the target. As our results show, incorporating pose will significantly improve the performance of the algorithm as pose has a direct influence on the observed RSSI readings. Although we do allow for pose to be continuous in that it can take any value between 0° and 360°, we only consider four orientations with respect to beacons when we apply our algorithms. Each additional orientation that we consider requires an additional set of data from scene analysis. This not only means that we require more data collection during an offline model building phase, but also results in increased computational costs. However, considering more granular orientations and/or improved likelihood formulations will improve accuracy at the expense of computational costs.

Notably, the computation of likelihoods only made use of the instantaneous RSSI readings, an improvement would be to include other measurements possible from radio waves. Examples include RSSI readings from multiple advertising channels help eliminate noisy channels or making use of other information that can be extracted from the signal such as phase and incorporating the estimation of channel properties to be part of the estimated state to account for dynamic variations in RSSI measurements due to changes in the environment.

Further, as illustrated in our measurement results in Figure 3 and Figure 4, tracking in narrow passages can benefit from propagation models that explicitly consider multi-path propagation as opposed to models that attempted to capture the variability or noise in RSSI measurements.

We leave the above studies as well as multiple deployments and testing in spatial tracking applications to understand the changes in human behavior of older people for future work.

ACKNOWLEDGMENTS

This research was supported by a grant from the Australian Research Council (DP160103039). The researchers would like to acknowledge Dr. Amit Lampit, NHMRC-ARC Dementia Research Fellow, University of Sydney, for his feedback into the development of the spatial tracking system.

REFERENCES

[1] Alaa Alhamoud, Arun Asokan Nair, Christian Gottron, Doreen Böhnstedt, and Ralf Steinmetz. 2014. Presence detection, identification and tracking in smart homes utilizing bluetooth enabled smartphones. In *IEEE 39th Conference on Local Computer Networks Workshops (LCN Workshops)*. 784–789.

[2] Branko Ristic Sanjeev Arulampalam. 2004. *Beyond the Kalman filter: Particle filters for tracking applications.* Artech House.

[3] M. S. Arulampalam, S. Maskell, N. Gordon, and T. Clapp. 2002. A tutorial on particle filters for online nonlinear/non-Gaussian Bayesian tracking. *IEEE Transactions on Signal Processing* 50, 2 (2002), 174–188.

[4] M Sanjeev Arulampalam, Branko Ristic, N Gordon, and T Mansell. 2004. Bearings-only tracking of manoeuvring targets using particle filters. *EURASIP Journal on Applied Signal Processing* 2004 (2004), 2351–2365.

[5] Fernando Caballero, Luis Merino, P Gil, Ivan Maza, and Aníbal Ollero. 2008. A probabilistic framework for entire WSN localization using a mobile robot. *Robotics and Autonomous Systems* 56, 10 (2008), 798–806.

[6] V. Chandel, D. Jaiswal, and A. Ghose. 2017. InLocW: A reliable indoor tracking and guiding system for smartwatches with path re-routing. In *IEEE International Conference on Pervasive Computing and Communications Workshops (PerCom Workshops)*. 697–702.

[7] Benjamin Charrow, Nathan Michael, and Vijay Kumar. 2015. Active control strategies for discovering and localizing devices with range-only sensors. In *Algorithmic Foundations of Robotics XI*. Springer, 55–71.

[8] TI Chowdhury, MM Rahman, Sadre-Ala Parvez, AKMM Alam, Abul Basher, Abusayeed Alam, and Shahriar Rizwan. 2015. A multi-step approach for RSSI-based distance estimation using smartphones. In *International Conference on Networking Systems and Security (NSysS)*. 1–5.

[9] Silke Feldmann, Kyandoghere Kyamakya, Ana Zapater, and Zighuo Lue. 2003. An Indoor Bluetooth-Based Positioning System: Concept, Implementation and Experimental Evaluation.. In *International Conference on Wireless Networks*. 109–113.

[10] Joana Barbosa Bastos Gomes. 2008. An overview on target tracking using multiple model methods. *Instituto Superior Tecnico* (2008).

[11] Yan Huang, Jianying Zheng, Yang Xiao, and Miao Peng. 2015. Robust Localization Algorithm Based on the RSSI Ranging Scope. *International Journal of Distributed Sensor Networks* 2015 (2015).

[12] Héctor José Pérez Iglesias, Valentín Barral, and Carlos J Escudero. 2012. Indoor person localization system through RSSI Bluetooth fingerprinting. In *International Conference on Systems, Signals and Image Processing (ICSSIP)*. 40–43.

[13] Martin Klepal, Stéphane Beauregard, and others. 2008. A novel backtracking particle filter for pattern matching indoor localization. In *Proceedings of the first ACM international workshop on Mobile entity localization and tracking in GPS-less environments*. 79–84.

[14] Pavel Kriz, Filip Maly, and Tomas Kozel. 2016. Improving Indoor Localization Using Bluetooth Low Energy Beacons. *Mobile Information Systems* 2016 (2016).

[15] Nan Li, Jiabin Chen, Yan Yuan, and Chunlei Song. 2016. A fast indoor tracking algorithm based on particle filter and improved fingerprinting. In *35th Chinese Control Conference (CCC)*. 5468–5472.

[16] X Rong Li and Vesselin P Jilkov. 2000. Survey of maneuvering target tracking: dynamic models. In *AeroSense*. 212–235.

[17] Guoqiang Mao, Barış Fidan, and Brian DO Anderson. 2007. Wireless sensor network localization techniques. *Computer networks* 51, 10 (2007), 2529–2553.

[18] Claudio Martella, Armando Miraglia, Marco Cattani, and Maarten van Steen. 2016. Leveraging proximity sensing to mine the behavior of museum visitors. In *IEEE International Conference on Pervasive Computing and Communications (PerCom)*. 1–9.

[19] Piotr Mirowski, Harald Steck, Philip Whiting, Ravishankar Palaniappan, Michael MacDonald, and Tin Kam Ho. 2011. KL-divergence kernel regression for non-Gaussian fingerprint based localization. In *International Conference on Indoor Positioning and Indoor Navigation (IPIN)*. 1–10.

[20] Filippo Palumbo, Paolo Barsocchi, Stefano Chessa, and Juan Carlos Augusto. 2015. A stigmergic approach to indoor localization using bluetooth low energy beacons. In *Advanced Video and Signal Based Surveillance (AVSS), 2015 12th IEEE International Conference on*. 1–6.

[21] Ling Pei, Ruizhi Chen, Jingbin Liu, Heidi Kuusniemi, Tomi Tenhunen, and Yuwei Chen. 2010. Using inquiry-based Bluetooth RSSI probability distributions for indoor positioning. *Journal of Global Positioning Systems* 9, 2 (2010), 122–130.

[22] Nissanka B Priyantha, Anit Chakraborty, and Hari Balakrishnan. 2000. The cricket location-support system. In *Proceedings of the 6th Annual International Conference on Mobile Computing and Networking*. 32–43.

[23] Aswin N Raghavan, Harini Ananthapadmanaban, Manimaran S Sivamurugan, and Balaraman Ravindran. 2010. Accurate mobile robot localization in indoor environments using bluetooth. In *IEEE International Conference on Robotics and Automation (ICRA)*. 4391–4396.

[24] Hongliang Ren and Max Q-H Meng. 2009. Power adaptive localization algorithm for wireless sensor networks using particle filter. *IEEE Transactions on Vehicular Technology* 58, 5 (2009), 2498–2508.

[25] Yongli Ren, Flora Dilys Salim, Martin Tomko, Yuntian Brian Bai, Jeffrey Chan, Kyle Kai Qin, and Mark Sanderson. 2017. D-Log: A WiFi Log-based differential scheme for enhanced indoor localization with single RSSI source and infrequent sampling rate. *Pervasive and Mobile Computing* 37, Supplement C (2017), 94 – 114.

[26] Rengamathi Sankarkumar and Damith C Ranasinghe. 2014. Watchdog: a novel, accurate and reliable method for addressing wandering-off using passive RFID tags. In *Proceedings of the 11th International Conference on Mobile and Ubiquitous Systems: Computing, Networking and Services*. 208–217.

[27] Santosh Subedi, Goo-Rak Kwon, Seokjoo Shin, Suk-seung Hwang, and Jae-Young Pyun. 2016. Beacon based indoor positioning system using weighted centroid localization approach. In *Eighth International Conference on Ubiquitous and Future Networks (ICUFN)*. 1016–1019.

[28] Fazli Subhan, Halabi Hasbullah, Azat Rozyyev, and Sheikh Tahir Bakhsh. 2011. Indoor positioning in bluetooth networks using fingerprinting and lateration approach. In *International Conference on Information Science and Applications*. 1–9.

[29] Philipp Vorst, Jürgen Sommer, Christian Hoene, Patrick Schneider, Christian Weiss, Timo Schairer, Wolfgang Rosenstiel, Andreas Zell, and Georg Carle. 2008. Indoor positioning via three different rf technologies. In *4th European Workshop on RFID Systems and Technologies (RFID SysTech)*. 1–10.

[30] Yapeng Wang, Xu Yang, Yutian Zhao, Yue Liu, and Laurie Cuthbert. 2013. Bluetooth positioning using RSSI and triangulation methods. In *IEEE 10th Consumer Communications and Networking Conference (CCNC)*. 837–842.

[31] David Young. 2014. Fundamentals of Beacon Ranging. http://developer.radiusnetworks.com/2014/12/04/fundamentals-of-beacon-ranging.html. (2014). Accessed: 2016-03-30.

[32] Mingyue Zhou and Damith C Ranasinghe. 2013. A novel approach for addressing wandering off elderly using low cost passive RFID tags. In *International Conference on Mobile and Ubiquitous Systems: Computing, Networking, and Services*. 330–343.

[33] Jianyong Zhu, Haiyong Luo, Zili Chen, and Zhaohui Li. 2014. RSSI based Bluetooth low energy indoor positioning. In *2014 International Conference on Indoor Positioning and Indoor Navigation (IPIN)*. 526–533.

[34] Yuan Zhuang, Jun Yang, You Li, Longning Qi, and Naser El-Sheimy. 2016. Smartphone-Based Indoor Localization with Bluetooth Low Energy Beacons. *Sensors* 16, 5 (2016), 596.