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Microlocation for Smart Buildings in the Era of the Internet of Things

A survey of technologies, techniques, and approaches

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Microlocation plays a key role in the transformation of traditional buildings into smart infrastructure. Microlocation is the process of locating any entity with a very high accuracy, possibly in centimeters. Such technologies require high detection accuracy, energy efficiency, wide reception range, low cost, and availability. In this article, we provide insights into various microlocation-enabling technologies, techniques, and services and discuss how they can accelerate the incorporation of the Internet of Things (IoT) in smart buildings. We cover the challenges and examine some signal processing filtering techniques such that microlocation-enabling technologies and services can be thoroughly integrated with an IoT-equipped smart building. An experiment with Bluetooth Low-Energy (BLE) beacons used for microlocation is also presented.

Overview of microlocation

The interconnectedness of all things is continuously expanding. The aim is to have every individual interconnected with his or her surroundings, whether it be at home, at work, or in public spaces. Some of these services might include but are not limited to indoor mapping and personalized environment changes, such as lighting and temperature settings, as well as directed advertisement. For these systems to perform, it is essential to have reliable hardware and accurate data. Outdoor localization technologies, such as the Global Positioning System (GPS), do not work indoors due to the physical barriers that block the signal and do not provide location data accurate enough for microlocation. Current solutions use received signal strength indication (RSSI) to determine position. A variety of solutions that use RSSI have been proposed to provide location services for indoor environments, though each solution presents its own drawbacks. Multiple technologies and techniques have been adapted to provide indoor location information, all of which attempt to overcome the noise and dynamics of a changing indoor environment.

A promising approach includes the effective use of the plethora of IoT devices that are available on the market. BLE

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beacons, usually referred to as *beacons*, are a promising candidate to improve indoor localization accuracy. They are small Bluetooth transmitters designed to attract attention to a specific location. As in many IoT-based networks, the performance of such networks relies on the network lifespan and accuracy. BLE beacons are a cheap, simple, and very scalable means of implementing indoor localization services. In recent years, BLE technology has grown in popularity, and much more research has been developed in using it for indoor localization [1]–[3]. The fundamental operation of these beacons for localization purposes is based on RSSI techniques, where the received RSSI value is translated into a distance by using a best curve fit signal propagation model. BLE beacon protocols, such as iBeacon [4] and Eddystone [5], provide the necessary information and configuration capabilities for microlocation. Along with the low power consumption of BLE, beacon devices are easily deployed and require low maintenance, hence their scalability for any complex indoor environment.

Intrinsic to any wireless technology, BLE beacons are highly susceptible to noise and interference. To overcome the effects of noise and dynamic changes in the physical environment, many methods devised around advanced positioning algorithms and filtering techniques have been adapted to beacon-based systems to improve the accuracy obtained in using RSSI localization techniques, as shown in Figure 1. Some of the most common filter implementations are Kalman filters, as detailed in [6]. Kalman filtering has also been examined in the context of indoor localization [7]. These filters provide a reasonably accurate state estimation and can be adjusted for changes is environmental/process noise. Other filters, such as particle filters (PFs), are also used. PFs are highly accurate but at the cost of greater computational complexity, hence the need for a client-server-based model, as outlined in [2] and [8]. Positioning algorithms can also have an effect on beacon accuracy. The work presented in [9] implements the K-nearest neighbor algorithm to calculate the position of the user. The experiments showed an average error of 1 m. Other algorithms, such as the pedestrian dead-reckoning approach, have been implemented with BLE beacons [10]. In these experiments, the integration of smartphone sensors for data regarding step detection, step direction, and walking length are combined with beacon calibration zones to provide a more accurate position. All techniques may provide different accuracy results and may behave differently depending on the environment, so it is important to note the characteristics of each tested environment when deciding on what technique to implement.

In this article, we survey available wireless technologies for microlocation systems in a smart building. Then we discuss signal processing techniques and characteristics that can be used to improve microlocation performance, along with filtering approaches. We focus on the use of BLE beacons, and, through an experiment, we discuss how they can enhance microlocation.

Smart buildings with IoT technologies

The IoT revolution has brought a swarm of continuously interconnected and sensor-packed devices opening a vast number of opportunities in equipping existing infrastructures. The IoT has enabled applications that transform facilities to intelligent spaces able to critically affect and improve the productivity and life quality of the occupants. Reducing energy costs and detecting and building knowledge based on human patterns as well as improving the human–building interaction are only some cases in point.

The Institute for Building Efficiency [11] defines smart buildings as buildings that can provide low-cost services, such as air conditioning, heating, ventilation, illumination, security, sanitation, and various other services, to tenants without adversely affecting the environment. This requires the collaboration of multiple sensors that form a building's IoT ecosystem. The basic motive behind the construction of smart buildings is to provide the highest level of comfort and efficiency. At the same time, the interconnection of the automation systems can assist with disaster management and provide emergency services. The collaboration of the fire system with the air conditioning system, e.g., can create an environment where a fire will not expand to the rest of the building.

To that end, indoor-focused location-based services (LBSs) are the fundamental components for providing a tenant-to-building interaction. LBSs provide the ability to efficiently track occupants in real time. They either attempt to estimate the user's two-dimensional (2-D) coordinates, which is referred to as *microlocation*, or they assign the user in the locality of certain points of interest, which is known as *proximity sensing.*

The integration of smart buildings with the IoT creates a number of challenges. A smart building with an IoT ecosystem requires three main components: the sensors, the integration, and the actuators. The sensors must be connected to a reliable, highly available network that optimally can self-diagnose and heal. Integration is probably the part where innovation is now taking place. It consists of some software that would receive the input from the sensors, process and

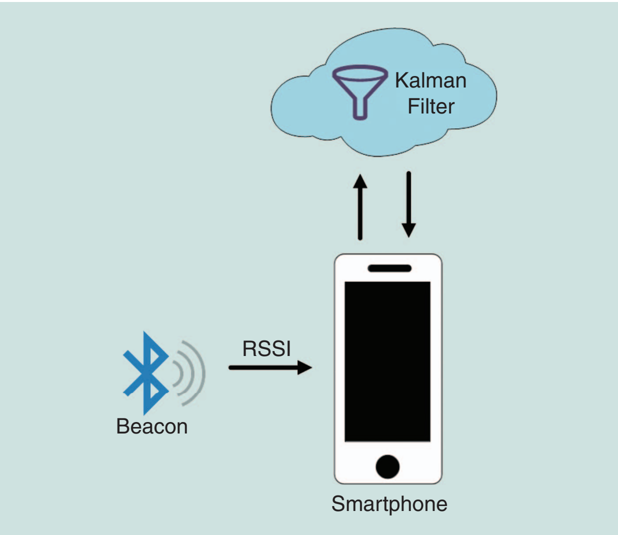

FIGURE 1. The microlocation system using the Kalman filter.

analyze, and provide some actuator as a service to the tenants, e.g., unlocking a door, switching on the TV, calling the elevator, or configuring the room temperature based on needs.

Overview of microlocation systems

Wireless technologies

Microlocation systems can leverage existing wireless infrastructure for microlocation to minimize the cost or may require a specific wireless deployment [1]. By *wireless technologies* we refer both to high-frequency technologies as well as low frequency. The most common high-frequency wireless technologies that have been used in a microlocation deployment are, e.g., Wi-Fi [12], Zigbee [13], radio-frequency identification (RFID) [14], and Bluetooth [15]. However, low-frequency technologies like the ones based on physical light have also seen some research and commercial use [16]. Light fidelity (Li-Fi), e.g., is one of the wireless technologies in the form of visible light communication (VLC) technology. These technologies have been used successfully in the past for indoor location and navigation, and their popularity among IoT devices makes them an ideal solution for microlocation as well. There are also technologies such as Wi-Fi HaLow [17], BLE version 5.0 [15], and LoRaWAN [18], which are specifically designed for IoT devices.

IEEE 802.11, Wi-Fi

The IEEE 802.11 standard [12], commonly known as *Wi-Fi*, is among the most popular technologies used for localization when GPS is inadequate. The great distribution of access points and signal availability at an indoor environment make it easy to collect the received signals from various access points and calculate the location of the receiver. The indoor transmission range can vary from 3.3 m with a bandwidth of 6.7 Gbit/s (IEEE 802.11ad), up to 70 m with a bandwidth of 600 Mbit/s (IEEE 802.11n), and it can operate in 2.4, 5, and 60 GHz.

Wi-Fi networks are deployed for communication; hence, data rate and connectivity are important, whereas localization is not their priority. Also, Wi-Fi networks are designed for a plethora of devices, from smartphones and laptops to phablets and smartwatches. This is a tradeoff for microlocation techniques. The availability of Wi-Fi signals and Wi-Fi-enabled devices is an advantage for microlocation as the number of portable devices and potential reference points for localization increases. Advanced signal processing techniques can be used to improve the quality of the Wi-Fi signals for localization. At the same time, there is no need for extra hardware deployment with Wi-Fi technology.

However, IoT devices have unique characteristics, such as size and limited energy resources, that are not taken into consideration for general Wi-Fi technology. As the number of these devices increases, the 2.4- and 5-GHz channels become overcrowded, whereas the interference increases with a drop in the network capacity. Unfortunately, traditional Wi-Fi was not originally designed to tackle these interference issues and the increasing capacity in dense environments. To fill this gap, the Wi-Fi Alliance announced the Wi-Fi HaLow (IEEE 802.11ah).

IEEE 802.11ah, Wi-Fi HaLow

Wi-Fi HaLow [17] was designed to enable connectivity to a variety of new power-efficient use cases in smart homes, smart cities, and connected vehicles and supporting the concept of the IoT in general. It extends Wi-Fi into the 900-MHz band to enable the low power connectivity that is necessary for IoT devices. The transmission range is twice the range of Wi-Fi, and it increases the signal robustness in challenging environments, such as complex indoor environments with lots of furniture and walls. It can operate in multiple transmission modes from low rates, starting from 150 and up to 347 kilobit/s.

The ability to operate in the low-power, high-transmission range and low propagation loss make Wi-Fi HaLow a good candidate for microlocation with IoT devices. However, it is relatively new in comparison with other technologies (published in 2017); hence, it is not widely available, and it will be a while before we see HaLow clients and infrastructure devices. This delays the experimentation that is necessary before deciding if it is suitable for microlocation.

Zigbee

Zigbee is a high-level communication protocol known for its simplicity, low power usage, and secure networking [13]. It is based on the IEEE 802.15.4 standard, which defines the operating point of wireless personal area networks (WPANs) with low-data-rate antennas. They are able to control the flow of information and prevent any loss of data by using carrier-sense multiple access with collision avoidance. Devices using Zigbee are designed with additional features, such as link quality and energy detection, that allow for measurements, such as the RSSI, to be easily determined. Zigbee is commonly used for localization in wireless sensor networks due to its low power requirements. Among IoT devices, though, it is not popular due to the extra hardware that is needed.

Bluetooth

Bluetooth is another wireless technology for exchanging data over short distances [15]. The IEEE standardized Bluetooth as IEEE 802.15.1 but no longer maintains the standard, which is managed by the Bluetooth Special Interest Group (SIG). According to the SIG, Bluetooth is all about proximity, not about exact location. Bluetooth was not intended to offer a pinned location like GPS. However, it is known as a *geofence* or *microfence solution*, which makes it an indoor proximity solution, not an indoor positioning solution.

Introduced by the Bluetooth SIG in 2010, BLE was designed for applications that do not require large amounts of data transfer, reducing the power consumption and cost of devices. Microlocation and indoor mapping have been linked to

Bluetooth and to the BLE-based iBeacon promoted by Apple [4]. Large-scale indoor positioning systems based on iBeacons have been implemented and applied in practice.

Similar to Zigbee, BLE is a technology used in WPANs. The low power consumption of BLE has led to a number of new devices in the IoT. BLE 4.0 can reach 25 Mbit/s at a distance of 60 m. Applications using BLE have greatly increased during the past couple of years. A number of new devices have been developed, in such fields as health care [19], sports, fitness, security, and home entertainment. One device that has been created is known as a *beacon*. Beacons are small, inexpensive devices that contain only a central processing unit, a radio, and batteries.

Bluetooth 5.0 [15] is the competitor of Wi-Fi HaLow in the IoT domain. It is claimed to have twice the speed of the previous version, four times longer transmission range, and exchange data eight times faster. The simplicity and popularity among IoT devices are advantages of Bluetooth for microlocation. The small size of beacons and their low cost with the energy efficiency of the BLE and the extended lifespan that it can provide can be used to enhance microlocation in a complex environment without interfering with other wireless infrastructures. For disadvantages, even though the security of BLE is good, it is even better on Wi-Fi.

RFID

RFID devices were primarily designed for data transfer and storage [14]. There is a need for an RFID reader that can communicate with RFID tags. There are two types of RFIDs. The active RFIDs operate in the ultrahigh frequency and microwave frequency ranges. They need to be connected to a local power source while they transmit their ID periodically up to 100 m. Passive RFIDs, however, operate without battery but within 1–2-m transmission range.

In the IoT era, RFID is not a promising solution for microlocation. Its accuracy is not high enough, and it is not available on many portable devices.

LoRaWAN

LoRaWAN is a long-range, low-power-consumption technology used in the development of personal wide area networks [18]. Originally developed by the LoRa Alliance, the LoRaWAN protocol transmits at a lower frequency of 915 MHz. The benefit of using a lower frequency is that the smaller wavelength allows for a greater distance that the signal can reach. Due to that, it can pass through walls and obstacles without issue. It is also no longer as easily susceptible to noise because it does not interfere with any devices transmitting on the 2.4-GHz band.

The disadvantage of using such a low frequency is a reduction in the data rate that can be sent between transmitting devices. For microlocation, this is not an issue, as the nodes are not transmitting large amounts of information. Due to the 915-MHz band being unlicensed, it is free for anyone to use for his or her personal networking needs.

For devices that are moving at high speed in a large area, LoRa might be a candidate for localization with the IoT. Unfortunately, in the short range, LoRa performance does not overcome the high cost and the extra equipment that are needed to set up a LoRa node.

Li-Fi

Li-Fi is a VLC technology [20]. VLC is a subset of optical wireless communication, which uses light-emitting diodes (LEDs) as a medium to enable high-speed communication. Data are transmitted by modulating the intensity of LED light at nanosecond intervals, too quick to be detected by the human eye.

Table 1 summarizes the specifications of each wireless technology along with the advantages and disadvantages of usage for microlocation.

Radio signal features for microlocation

As the wireless signal propagates from the sender to the receiver, there are signal characteristics that can be used for the

Table 1. The wireless technologies for microlocation.

Technology	Throughput	Transmission Range	Power Consumption	Advantages	Disadvantages
IEEE 802.11ac	3.5 Gbit/s	35 m	Moderate	Available in many environments	Prone to noise and interference
IEEE 802.11ad	6.7 Gbit/s	3.3 m			
IEEE 802.11ah	347 Mbit/s	1 km	Low	Wide reception range	Not widely available
Zigbee	250 kbit/s	75 m	Low	Easy to set up	Extra hardware
BLE v4.0	25 Mbit/s	60 m	Low	High throughput	Prone to interference
BLE v5.0	50 Mbit/s	240 m			
RFID active	1,067	100 m	Low	Low power	Low accuracy
RFID passive	1,067	2 m			
LoRaWAN	50 kbit/s	15 km	Extremely low	Wide range	Extra hardware
Li-Fi	1 Gbit/s	10 m	Low	Dense environments	Low range

localization of one of the communicating devices. There are four main signal features that can be used for localization.

RSSI

RSSI is one of the most commonly used characteristics for indoor localization [1]. It is based on measuring the power present in a received signal from a client device to an access point. As radio waves propagate according to the inverse-square law, the distance can be approximated based on the relationship between transmitted and received signal strength, as long as no other errors contribute to faulty results. The combination of this information with a propagation model can help to determine the distance between the client device and the access points. Lateration-based methods are commonly used along with RSSI to estimate the location of the client.

It can be assumed that the more access points, the more information can be collected, and hence the accuracy can be increased. This, however, works also as a tradeoff. An increase of the access points will also increase the interference between different signals. A key challenge in wireless localization systems is that the range measurements are often associated with errors. Although RSSI techniques are among the cheapest and easiest methods to implement, the disadvantage is that RSSI does not provide very good accuracy, with a median of 2–4 m. This is mainly because the RSSI measurements tend to fluctuate according to environmental changes or multipath fading, events that are common in indoor environments.

Angle of arrival

Angle of arrival (AoA) is another characteristic that can be used for localization. It tries to estimate the direction of the signal propagation, i.e., the angle from which the signal arrives at a receiver. AoA is typically achieved by using an array of antennas. The line connecting two reference points may be used as an internal reference. The spatial separation of antennas leads to differences in arrival times, amplitudes, and phases.

Time of arrival

In time of arrival (ToA) (also known as *time of flight*), the distance between the sender and receiver of a signal can be determined using the measured signal propagation time and the known signal velocity. ToA is the amount of time a signal takes to propagate from transmitter to receiver. The signal propagation rate is constant and known; hence, the travel time of a signal can be used to directly calculate distance. This is the technique used by GPS.

The accuracy of the ToA-based methods often suffers from massive multipath conditions in indoor localization, which is caused by the reflection and diffraction of the RF signal from objects (e.g., interior wall, doors, or furniture) in the environment. However, it is possible to reduce the effect of multipath by applying temporal or spatial sparsity-based techniques.

Time difference of arrival

The time difference of arrival (TDoA) is the ToA of a specific signal at physically separate receiving stations with precisely synchronized time references. TDoA measures the difference in ToA at two different receivers. Three or more TDoA measurements can be used to locate a device with hyperbolic lateration.

Although TDoA sounds similar to ToA, there is a difference. In ToA, the absolute time at a base station is used. In TDoA, the measured time difference between departing from one and arriving at the other station is used.

Indoor positioning techniques

Proximity detection

Proximity detection techniques, shown in Figure 2(a), are based on the proximity of the mobile device to previously known locations. These techniques determine the position of an object based on closeness to a reference in the physical space. When the mobile device receives the signal from a reference point, then the device should be within the coverage range of the reference point, i.e., in close proximity to the reference point. Proximity detection does not provide the location in the form of coordinates but rather in the form of sets of possible locations.

This method is also based on the premise that the reference point has a limited range. For simplicity, it is common to assume that the range of a wireless infrastructure would be well represented by a circle of given radius r. Then, the result of the proximity detection would be located inside this circle. For several circles, one can limit the possible location to the intersection of the different circles.

Lateration

Lateration is the process of estimating the location of a mobile device's given distance measurements to a set of points with a known location, shown in Figure 2(b). Lateration-based methods use the distance measurements from multiple reference points to compute the position of a receiver. Trilateration is a commonly used technique to calculate the estimated client device position relative to the known position of three access points. It uses the distance from the three reference points to estimate the location and track the position of the receiver when the receiver is moving within the three points. Given the distance to an anchor, it is known that the node must be along the circumference of a circle centered at the anchor and a radius equal to the node–anchor distance. In 2-D space, at least three noncollinear anchors are needed; in three-dimensional space, at least four noncoplanar anchors are needed.

Angulation

Angulation-based positioning techniques can be used to employ the AoA of a wireless signal and determine the position of a receiver, as shown in Figure 2(c). A commonly used approach is triangulation, where the location of a point is determined by forming triangles to it from known points. In

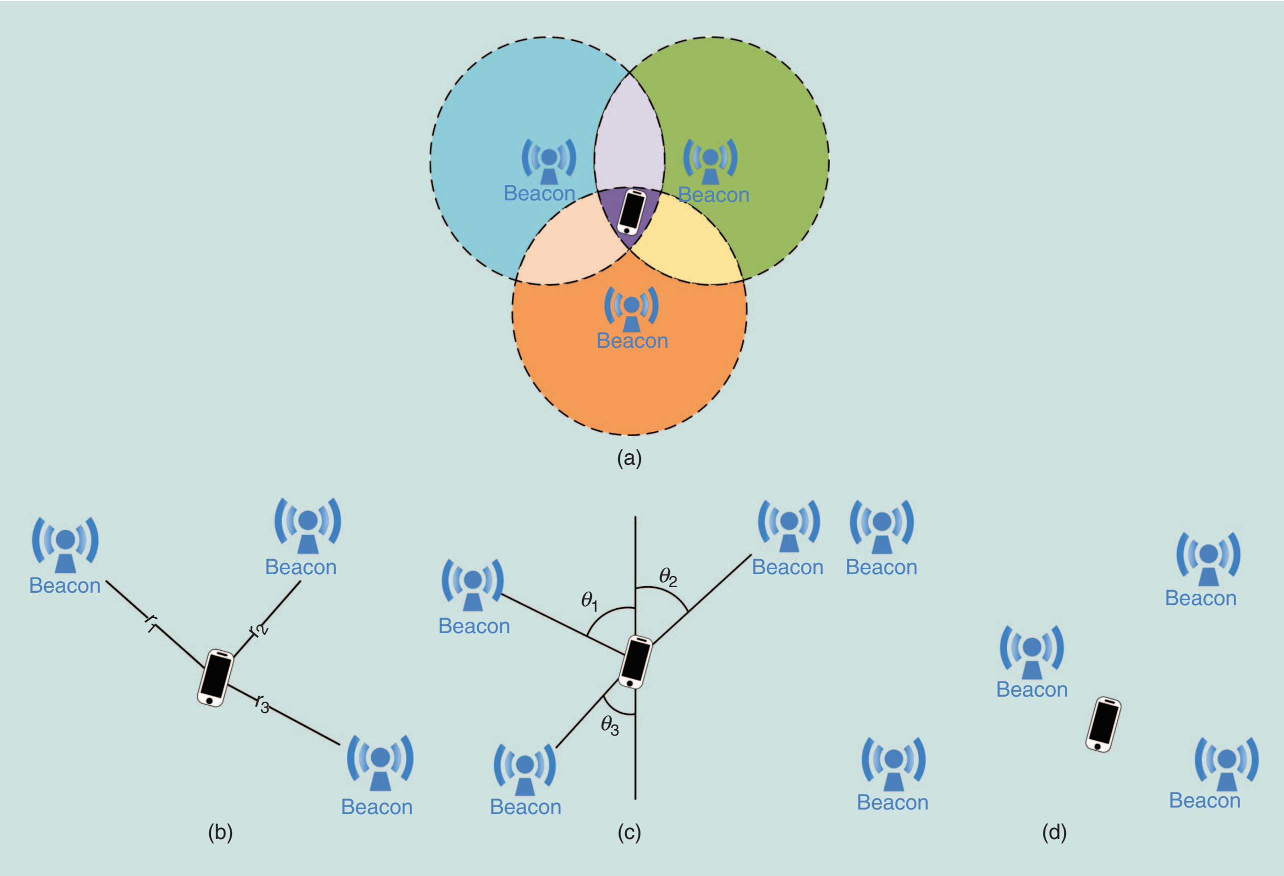

FIGURE 2. The localization techniques: (a) proximity, (b) lateration, (c) angulation, and (d) fingerprinting.

triangulation, a known baseline can be used to find the location relative to two anchor transmitters. It uses the geometric properties of triangles to estimate the location and relies on angle (bearing) measurements. It requires a minimum of two bearing lines and the locations of anchor nodes or the distance between them for 2-D space.

Fingerprinting

Fingerprinting techniques are based on the reproducibility of patterns of measurable variables, shown in Figure 2(d). Traditional fingerprinting records the signal strength from several access points and stores them in a database, along with the known coordinates of the client device in an offline phase. Then, during the localization phase, the current vectors at an unknown location are compared to those in the database, and the closest match is returned as the estimated user location.

Fingerprinting has the advantage that it does not require any assumption regarding the nature of the propagation environment. It just creates a model environment based on the training data. At the same time, this can be a disadvantage. Any change of the environment, such as adding or removing furniture or access points, requires an update to the model.

Localization metrics

To evaluate the performance of a localization system, accuracy and precision are used. Accuracy measures the deviation of the estimated location from the truth, whereas precision measures the deviation of location estimates from each other for the same location. A system with high accuracy can be used for an application that focuses on long-term localization determination, and the errors cancel out over time. A system with high precision can be used to find the proximity between devices, but it is hard to use for localization.

Improve accuracy through signal processing filtering techniques

There are a number of signal processing filtering techniques that are used for indoor localization. In the following, we summarize two: Kalman filtering and dynamic Kalman filtering.

Indoor localization model

We model the indoor localization problem as posed by Arulampalam et al. [21]. Extended versions as applied in BLE can also be found in [7]. Because we seek to estimate the user position/state under a set of measurements obtained in a typical noisy indoor environment, Bayesian filtering is an attractive approach for such problems. However, Bayesian filtering requires the following two models.

1) *System model*: A system model describes the variation of the state (user position in our case) with time. The system model relates the position vector y_i with the process noise m_i and previous state.

2) *Measurement model*: A measurement model relates the noisy measurements (RSSI for PF and the user position for extended Kalman filtering) with the state/position.

We construct the posterior probability density function (pdf) describing the state from all available information, including the measurements from the reference nodes (beacons in our case). The pdf is considered as the complete solution to the state estimation problem because it contains all of the required information. The problem involves recursively estimating the user state/position as we receive measurements from the beacon. Therefore, we require a recursive filter. Recursive filters consist of the prediction and update stage in which the state is predicted and then updated once the measurements are available. The presence of noise in indoor settings affects the position calculation, so the pdf is usually distorted. The obtained measurements in the update state are used to modify the prediction pdf using Bayes' theorem.

Mathematically, state y_i at time i is a function of the state at time step $(i–1)$ as well as the process noise m_{i-1} [22], as described in (1):

$$y_i = f_i(y_{i-1}, m_{i-1}). \tag{1}$$

The nonlinear function $f_i: \Re^{n_y} \times \Re^{n_m} \to \Re^{n_y}$ (as indoor localization is a nonlinear problem) relates the previous state y_{i-1} and process noise m_{i-1} with the current state *yi* as described by Arulampalam [21]. The sequence $\{m_i, i \in \aleph\}$ represents an independent and identically distributed (i.i.d.) process noise sequence. The integer n_y represents the state noise vector, and n_m represent the process noise vector. The set of natural numbers is represented by $\aleph$. The measurement model relates the obtained measurement x_i to the state y and measurement noise n at time i [22] as given in (2):

$$x_i = h_i(y_i, n_i). \tag{2}$$

The mapping function $h_i: \Re^{n_y} \times \Re^{n_n} \to \Re^{n_x}$ can be either linear or nonlinear. Functions f_i and h_i rely on the laws of motion/physics. The sequence $\{n_i, i \in \aleph\}$ is a measurement noise sequence that is i.i.d. The integers n_x and n_n represent the measurement and measurement noise vectors dimension, respectively.

Recursively calculating the pdf $p(y_i | x_{1:i})$ allows us to continuously calculate the belief in the state y_i at any particular time instance i in the presence of noisy measurements. The initial pdf $p(y_o | x_0)$ is assumed to be equivalent to the state vector's prior $p(y_0)$ [21]. We assume that the prior is available. The available information is enough to calculate the pdf $p(y_i | x_{1:i})$ recursively in the prediction and update stages. In the prediction stage, if the pdf $p(y_{i-1} | x_{1:i-1})$ is available, we can use the Chapman–Kolmogorov equation given in (3) to obtain the prior pdf of the state at any time instance i:

$$p(y_i | x_{1:i-1}) = \int p(y_i | y_{i-1}) p(y_{k-1} | x_{1:i-1}) dy_{i-1}. \tag{3}$$

At any time instance i, we collect the observations x_i from the sensors to update the prior using Bayes' rule given in (4) [21]. The denominator in (4) is explained in (5):

$$p(y_i | x_{1:i}) = \frac{p(x_i | y_i) p(y_i | x_{1:i-1})}{p(x_i | x_{i-1})}, \tag{4}$$

$$p(x_i | x_{i-1}) = \int p(x_i | y_i) p(y_i | x_{i-1}) dy_i. \tag{5}$$

The collected measurements x_i in the update stage are then used to update the prior density, resulting in the required current state's posterior density. Recursively updating the system using (3) and (4) results in an optimal Bayesian solution. However, analytically, it is not possible to obtain the recursive propagation of posterior probability density as done in (3) and (4). Therefore, a number of different algorithms, including PF, Kalman filter, and extended Kalman filter, are used to obtain a solution.

Kalman filter

The Kalman-filter-based RSSI smoother is based on the work of Guvenc [23]. The state x_i, which in our case consists of RSSI and rate of change of RSSI, at time i is a function of the state at time i–1 and the process noise w_{i-1}, which is given mathematically by (6). The obtained RSSI measurements z_i at instant i from the iBeacons is a function of the state at i–1 and the measurement noise v_i as given by (7), as described in Arulampalam [21]:

$$x_i = f(x_{i-1}, w_{i-1}), \tag{6}$$

$$z_i = h(x_{i-1}, v_i). \tag{7}$$

The traditional Bayesian-based approach consists of the prediction and update stage, as described by Guvenc [23], and is given as follows:

1) prediction stage:

$$p(x_i | z_{1:i-1}) = \int p(x_i | x_{i-1}) p(x_{i-1} | z_{1:i-1}) dx_{i-1}. \tag{8}$$

2) update stage:

$$p(x_i | z_{1:i}) = \frac{p(z_i | x_i) p(x_i | z_{1:i-1})}{p(z_i | z_{1:i-1})}, \tag{9}$$

where

$$p(z_i | z_{1:i-1}) = \int p(z_i | x_i) p(x_i | z_{1:i-1}) dx_i. \tag{10}$$

We assume that both the process noise and measurement noise are Gaussian and the functions f and h in (6) and (7) are linear. As a result of the linearity assumption, we can apply a Kalman filter because it is the optimal linear filter.

Due to the aforementioned assumptions, (6) and (7) can be rewritten as described by Guvenc [23]:

$$x_i = F x_{i-1} + w_i, \tag{11}$$

$$z_i = H x_i + v_i, \tag{12}$$

where $w_i \sim N(0, Q)$ and $v_i \sim N(0, R)$. Table 2 lists the parameters of a Kalman filter. The prediction and update stages for the Kalman filter as described by Guvenc [23] are

1) prediction stage:

$$\hat{x}_{\bar{i}} = F\hat{x}_i, \tag{13}$$

$$P_{\bar{i}} = FP_{i-1}F^T + Q. \tag{14}$$

2) update stage:

$$K_i = P_{\bar{i}}H^T(HP_{\bar{i}}H^T + R)^{-1}, \tag{15}$$

$$\hat{x}_i = \hat{x}_{\bar{i}} + K_i(z_i - H\hat{x}_{\bar{i}}), \tag{16}$$

$$P_i = (I - K_iH)P_{\bar{i}}. \tag{17}$$

The higher the Kalman gain, the higher will be the influence of the measurements on the state. The prediction and update steps are recursive in nature.

For the purpose of filtering the RSSI values, we use a state vector x_i that consists of the RSSI value y_i and the rate of change of RSSI Δy_{i-1} as follows: $x_i = \begin{bmatrix} y_i \\ \Delta y_i \end{bmatrix}$.

Depending on the environment, Δy_i signifies how drastically RSSI value fluctuates. The higher the noise in the environment, the higher will be the fluctuation. The current value of RSSI y_i is assumed to be the previous RSSI y_{i-1} plus the change Δy_i and process noise w_i^y. Hence (11) can be written as

$$\begin{bmatrix} y_i \\ \Delta y_i \end{bmatrix} = \begin{bmatrix} 1 & \delta t \\ 0 & 1 \end{bmatrix} \begin{bmatrix} y_{i-1} \\ \Delta y_{i-1} \end{bmatrix} + \begin{bmatrix} w_i^y \\ w_i^{\Delta y} \end{bmatrix}, \tag{18}$$

which means that the state transition matrix F is given by

$$F = \begin{bmatrix} 1 & \delta t \\ 0 & 1 \end{bmatrix}.$$

The parameter δt is to be adjusted as per the variation in RSSI, which depends on the environment. For our set of experiments, δt was taken as 0.2 (using trial and error). Similarly, (12) can be rewritten as

$$[z_i] = [1 \;\; 0] \begin{bmatrix} y_i \\ \Delta y_i \end{bmatrix} + [v_i^y]. \tag{19}$$

The observation matrix H is given by

$$H = [1 \;\; 0].$$

Parameters P, Q, and R used in the experiments were obtained using trial and error and are as follows:

$$P = 100\mathbf{I}_{22}, \;\; Q = 0.001\mathbf{I}_{22}, \;\; R = [0.10].$$

The Kalman filter, once calibrated, effectively smooths the RSSI values. The smoothed RSSI values were then input into the path-loss model to obtain distances between the iBeacons and the user, and the user's proximity to the beacon was classified in any of the aforementioned zones.

Table 2. The Kalman filter parameter notation.

Symbol	Meaning
x	State vector
z	Measurement/observation vector
F	State transition matrix
P	State vector estimate covariance or error covariance
Q	Process noise covariance
R	Measurement noise covariance
H	Observation matrix
K	Kalman gain
w	Process noise
v	Measurement noise

Dynamic Kalman

A dynamic variation of the Kalman filter computes Q as the variance of a set number of previously collected RSSI values to make up for real-world process noise changes. It is continuously recalculated at each iteration of reading in the next RSSI value.

Different set sizes of recorded RSSI values can be used to find the ideal number of values to use in this calculation. It can be inferred that as the array size increases, the accuracy increases as well, up to an array size of n. After a size of n, any increase of the size leads to a decrease of the accuracy. The optimal n can be found through experimentation, whereas the increase of the size can lead to waste of resources without any increase in the accuracy. At the same time, a decrease of the size below n does not give sufficient information to the system to increase its prediction accuracy.

The set of RSSI values is stored in an array list of data type double. Algorithm 1 illustrates the procedure. It adds entries to each index in increasing order starting from index 0. When an entry is deleted, all entries ahead get pushed down one index value. At the start of each iteration, the algorithm checks the size of the array; once it reaches the desired size n, it removes the oldest entry (index 0) and adds in the newest measurement.

When developing the dynamic noise component of the Kalman filter, it is essential to find the ideal number of previously obtained RSSI values to maintain, for calculation purposes. This is because the size of this set will have a direct impact on the performance of the filter.

Algorithm 1. Maintain RSSI set.

1: **if** *RSSIArray.size*() == *n* **then**
2: *removeRSSIArray*[0].
3: *lastIndex* ← *RSSIArray.size*()
4: *RSSIArray*[*lastIndex*] ← *newRSSI*

BLE beacon technology

BLE beacons

BLE beacons are small wireless transmitters that broadcast their identifier to nearby electronic devices, such as smartphones, wearables, and other IoT devices. An analogy of the way beacons work is with the operation of a lighthouse. The lighthouse represents a known location that can be uniquely identified by its light. All of the ships that can see the light know about the existence of the lighthouse. However, the lighthouse neither communicates with the ships, nor does it know how many ships see its light or how many other lighthouses are in the area. Similarly, every beacon is sending out a radio signal to inform all of the radio-enabled devices in its range that the beacon is there. It does not know how many beacons or receiving devices are in the area, and it does not connect with them. An example of beacon operation is shown in Figure 3.

Beacons broadcast signals at a certain interval and within a certain transmission range. A beacon broadcasts a signal to all nearby devices that can receive the Bluetooth signal, i.e., the devices that have a Bluetooth receiver and the receiver is on. To collect the signal from the beacon, it is necessary to have a device with a BLE receiver. This can be a smartphone or a single-board computer, such as a Raspberry Pi. Applications or functions can be implemented based on the signal from the beacons. However, these applications are running on the hosting device, i.e., a smartphone or a Raspberry Pi, and not on the beacon.

Beacons are using BLE. The way the peripheral device announces its existence to the other devices is the opposite of how it is in the original Bluetooth classic. BLE enables a peripheral device to transmit an advertisement packet without being paged by the master/central device [24]. Due to this communication model, it is possible to construct energy-efficient transmitters. Moreover, when two BLE 4.0 devices are paired, they waste less battery power because the connection is dormant unless critical data are being shared. With the previous generation of Bluetooth, it was best to shut down your hardware when it was not in use. The Bluetooth SIG estimates between one and two years of battery power in some devices with Bluetooth 4.0.

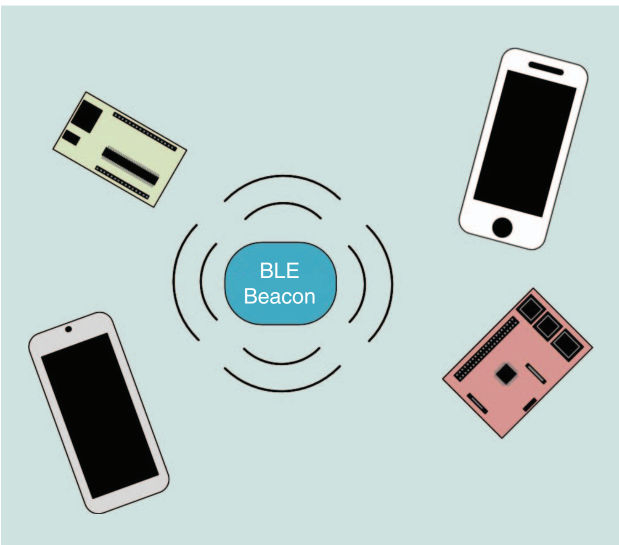

FIGURE 3. A BLE beacon broadcasting a signal to nearby devices. Each device can receive the signal and take an action in response.

Configuration parameters

BLE beacons have configuration parameters and a set of values that can determine their performance and utility for different applications. Some of these parameters are important when beacons are used in microlocation applications.

Transmission power

Transmission power is the required power to broadcast the beacon signal. As in every wireless device, transmission power directly affects the transmission range. The higher the transmission power, the longer the signal range of the beacon. This is an important tradeoff for most beacon applications. Technically, a beacon's range can reach up to 70 m. However, the battery might last for only six months. If the transmission range is constrained to 2 m, then the beacon might go up to two years without the need for battery replacement. A small transmission power can also increase the required number of beacons to cover an area, whereas a large transmission power can increase the collisions and interference. As can be inferred, an optimal transmission range can help to extend the lifetime of the beacons and minimize the battery replacement cost. At the same time, it can minimize unnecessary collisions with other beacons in the area.

Advertising interval

Advertising interval is another characteristic that affects the overall performance of beacons. It describes the time between consecutive transmissions. Applications that need to notify or detect the users that are moving in the area require a short advertising interval, and applications where the users are moving less frequently might improve their performance with a longer advertising interval. Similar to transmission power, the advertising interval affects beacon performance. The shorter the interval, the more stable the signal from the beacon. At the same time, the shorter the interval, the higher the power consumption. Once again, there is a tradeoff between beacon performance and power consumption.

BLE beacon protocols

Beacon protocols are standards of BLE communication. Each protocol describes the structure of the advertisement packet beacon's broadcast. It is necessary for the advertisement packet to have the media access control address of the beacon. There are different protocols, the most popular of which are the following.

- *iBeacon*: Apple's iBeacon was the first BLE beacon technology to come out [4]. iBeacon is a proprietary, closed standard. It broadcasts four pieces of information: 1) a universally unique identifier that identifies the beacon, 2) a major number identifying a subset of beacons within a large group, 3) a minor number identifying a specific beacon within the subset, and 4) a transmission power level in the major number's complement, indicating the signal strength 1 m from the device. This number must be calibrated for each device by the user or manufacturer. iBeacon has a simple implementation and large documentation, but it has fewer features in comparison with the following protocols. iBeacon works with iOS and Android but is native to iOS.

- *Eddystone*: Eddystone was announced from Google, and it is another protocol that defines a BLE message format for proximity beacon messages [5]. Eddystone protocol is able to transmit four different frame types: 1) a unique identifier, which is used to identify the individual beacon; 2) a uniform resource locator, which can be a website link that redirects to a website that is secured using secure sockets layer, eliminating the need for a mobile app; 3) telemetry, which includes sensor and administrative data from the beacon through telemetry, e.g., the beacon's battery level and its temperature; and 4) an encrypted identifier, which is an encrypted ephemeral identifier that changes periodically at a rate determined during the initial registration with a web service. This frame type is intended for use in security- and privacy-enhanced devices. Eddystone also works with both iOS and Android.
- *AltBeacon*: AltBeacon is an open-source beacon protocol [25] that was designed by Radius Networks. It has the same functionality as an iBeacon, but it is not company specific. This makes AltBeacon compatible with any mobile operating platform and more flexible because it has a customizable source code.
- *GeoBeacon*: GeoBeacon is another open-source beacon protocol, designed for usage in geocaching applications [26]. It has a very compact type of data storage. GeoBeacon can provide high-resolution coordinates, and it is also compatible with different mobile operating platforms.

Hardware solutions

There are a great variety of BLE beacon devices on the market. Most of them operate on batteries, such as Estimote, Kontakt, Gimbal, Glimworm, and BlueCats [27], but there are also solar-power beacons, such as the CYALKIT-E02. Each has its own unique features, such as additional sensors, battery life, reconfigurability, and dimensions, though all fundamentally work the same.

At the physical layer, BLE transmits in the 2.4-GHz industrial, scientific, and medical band with 40 channels, each 2-MHz wide. From those channels, 37 are used to exchange the data among paired devices, and three channels are designated for broadcasting advertisements. These three channels are primarily used by beacons and are chosen deliberately to minimize any collision with the Wi-Fi channels. A beacon broadcasts its advertisement packet repetitively based on the selected advertising interval while hopping over the three designated channels [28].

Beacon advantages for microlocation

Beacons have several advantages for use for microlocation.

- *Size*: Beacons are small in size and hence can be placed in almost any indoor environment with no problem. They can be placed behind the ceiling, under objects, or even on the walls.
- *Energy efficiency*: The great advantage of beacons comes from the energy efficient BLE protocol. At the same time, as the market of the beacons increases, so do the different design approaches. There are small beacons that work with one single coin cell battery, there are beacons with two AA batteries, and there are solar-powered beacons [29]. The lifetime of these beacons can be up to two years without the need for battery replacement [27].
- *Cost*: Most of the beacons in the market are cheap. Many beacons can be placed in a complex indoor environment to improve microlocation with minimum cost.
- *Interferences*: Beacons use BLE, and they will not interfere with other wireless infrastructures in the area.
- *Passive mode*: Beacons are broadcasters that do nothing else besides sending a piece of information. The logic behind each signal is done by the supporting device, such as a smartphone. Beacon signals are used by applications to trigger events and call actions, allowing the users to interact with physical things. All of the implementation is done on the device, and the beacons just broadcast the signal.
- *Platform independent*: Beacons can be used with iOS and Android devices. Each platform requires different protocols that have different packet layouts, but most platforms are able to listen to the different protocols.

Using BLE beacons for microlocation

Test case

Museums and art galleries usually provide visitors with either paper booklets or audio guides. Unfortunately, interest may vary from person to person, and each visitor's experience is also related to the available time to visit most of the exhibits. Interactive and personalized museum tours need to be developed. BLE beacons as a newly emerged technology can enhance a visitor's experience through microlocation, as shown in Figure 4.

Beacons can offer museums an opportunity to provide context to visitors through a smartphone application. Microlocation technology can make locating an exhibit much easier; at the same time, it can provide personalized suggestions to the user regarding the available exhibits. A mobile application can be developed that interacts with the available beacons.

When visitors are close to an exhibit, they can get all of the necessary information about the exhibit on their smartphone or

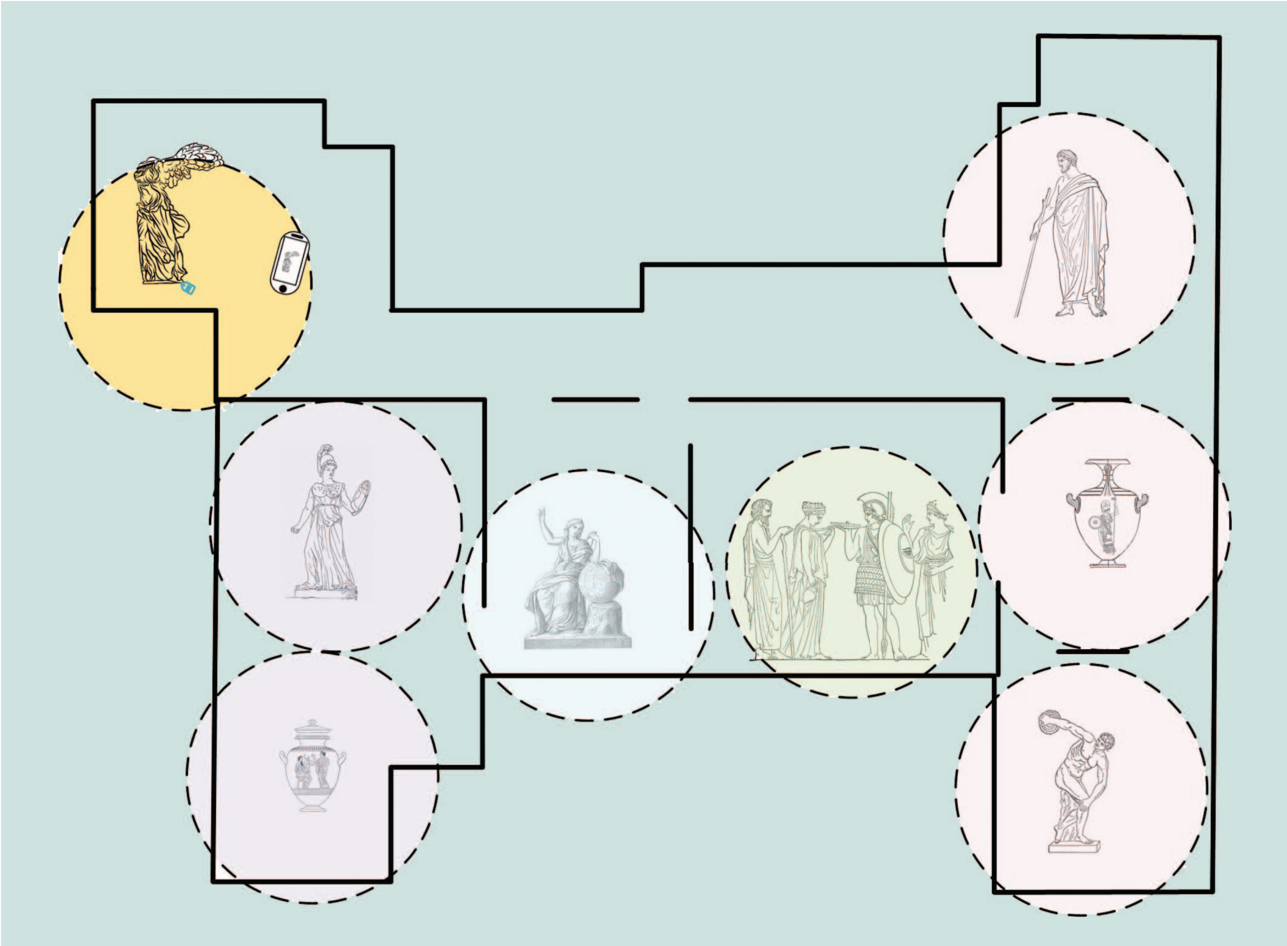

FIGURE 4. The BLE beacons used in an interactive museum scenario.

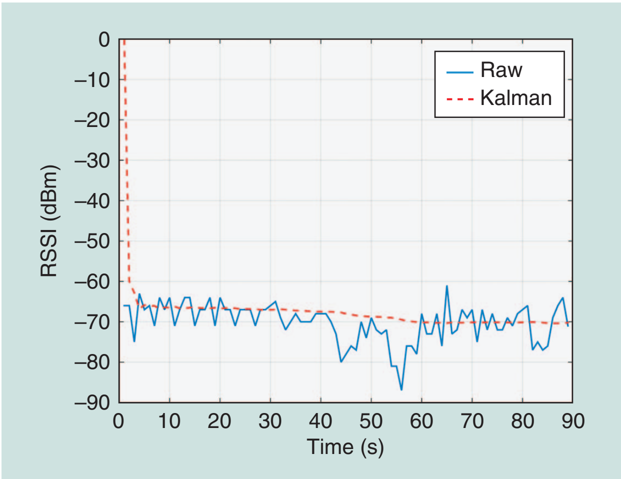

FIGURE 5. The received RSSI values 2 m from the BLE beacon.

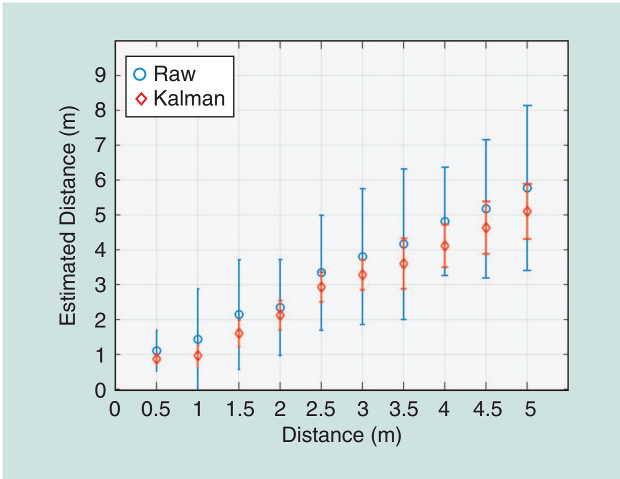

FIGURE 6. The distance estimation in ten different spots from the BLE beacon.

BLE-enabled mobile device in general. The application can also provide a recommendation to the visitor on the next exhibit he or she can visit, based on current location and interest. At the same time, the application can provide an optimal tour of the museum based on each individual's preferences. Beacons will also provide useful analytics to the museum. The number of visitors per exhibit can be collected, without violating visitor privacy. These analytics can be used to improve exhibit visibility.

The use of beacons provides several advantages for the museum and the visitors.

- *Promote exploration*: The application can encourage users to visit exhibits in different places of the museum.

Usually, visitors tend to spend most of their time in exhibits near the entrance, missing the opportunity to explore exhibits across all of the museum. Microlocation can help them identify more quickly the rooms in which they are interested.

- *Personalized tour*: When a user is interested in an exhibit, the application can provide a guided tour based on that interest. An interactive and personalized tour with exhibits from the same chronological period or within the same interest category can be provided to the user, who might miss them without the application.
- *Tour optimization*: For many visitors, the available time to spend in the museum is limited. The real-time analytics from the beacons can be used to provide an optimal route for the visitor, based on the available time for the visit.
- *Data analytics*: Beacon analytics can be used to improve the general visitor experience. There are exhibits that are missed due to their location, and there are exhibits that are overcrowded during a specific time of the day. Analytics can be used to optimize both cases and enhance the visitor experience.

Experimental results

In this section, we showcase the performance of the BLE beacons through a simple experimentation. We used BLE beacons from Gimbal Series 21 to examine the proximity estimation performance along with a smartphone, which was used to collect the signals [30]. The Kalman filter was applied on the collected data offline.

The Kalman filter estimation is shown in Figure 5. These are the collected RSSI values when the smartphone is 2 m away from the beacon. It is clear that the Kalman filter can minimize the effect of interference between the beacon and the smartphone, such as when people are moving between the two communicating devices.

To examine the performance of the Kalman filter, we placed the smartphone at ten different distances, starting from 50 cm and up to 5 m, increasing the distance 50 cm every time. In every location, we collected data on the smartphone for approximately 2 min. The average RSSI values are shown in Figure 6. When the smartphone is close to the beacon, the accuracy is high enough without filtering. As the distance increases, the accuracy without filtering decreases, and the standard deviation of the data increases as well. Interference and noise affect the data transmission; hence, as the distance between the communicating devices increases, these factors increase as well. Kalman filtering helps to keep the data close to the real value, and the standard deviation is smaller. The use of Kalman filtering helps minimize the effect of random noise and interference during the experiment.

We further examined the error between the estimated distance and the real distance and the number of occurrences of each group of errors, as shown in Figure 7. Without filtering, the error is within 3 m from the real location when distances up to 5 m are tested. In many applications that use microlocation, such as the test case, the location error should be smaller. A

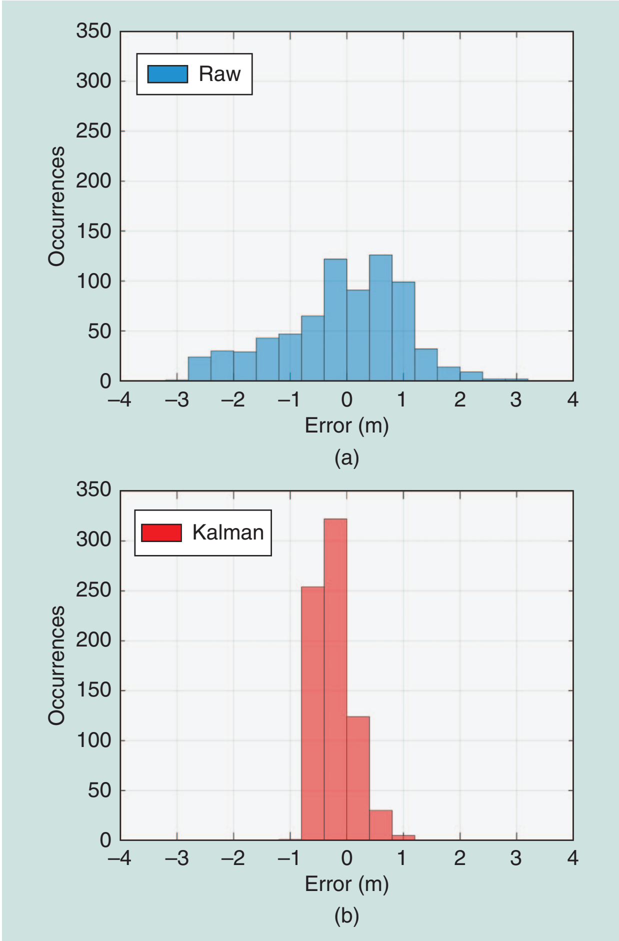

FIGURE 7. A histogram of experimental error: (a) raw data and (b) Kalman filter.

smaller error comes when the Kalman filter is used. The error is within 1 m from the real location, which can be acceptable for many microlocation applications.

Concluding remarks

This article provides an overview of wireless technologies that can be used for microlocation in smart buildings with the use of IoT devices. BLE is among the most energy-efficient technologies. BLE beacons are small, low-cost devices that can be used for localization. Unfortunately, they are prone to interference due to their wireless nature. Signal processing techniques, such as Kalman filters, can be used to enhance their performance.

A case study of BLE beacons in an interactive museum was also discussed. According to the experimental results, signal processing techniques can enhance beacon performance and provide accurate microlocation in the era of the IoT.

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