Chapter 6

Radio Frequency-Based Indoor Localization in Ad-Hoc Networks

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Additional information is available at the end of the chapter

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Abstract

The increasing importance of location-aware computing and context-dependent information has led to a growing interest in low-cost indoor positioning with submeter accuracy. Localization algorithms can be classified into range-based and range-free techniques. Additionally, localization algorithms are heavily influenced by the technology and network architecture utilized. Availability, cost, reliability and accuracy of localization are the most important parameters when selecting a localization method. In this chapter, we introduce basic localization techniques, discuss how they are implemented with radio frequency devices and then characterize the localization techniques based on the network architecture, utilized technologies and application of localization. We then investigate and address localization in indoor environments where the absence of global positioning system (GPS) and the presence of unique radio propagation properties make this problem one of the most challenging topics of localization in wireless networks. In particular, we study and review the previous work for indoor localization based on radio frequency (RF) signaling (like Bluetooth-based localization) to illustrate localization challenges and how some of them can be overcome.

Keywords: ad-hoc networks, wireless sensor networks (WSNs), localization, radio frequency (RF) signaling, Bluetooth low energy (BLE), Wi-Fi, XBee, indoor localization, range-based localization

1. Introduction

Localization is a key requirement of most mobile and wireless networks. For example, wireless sensor networks are often deployed in an ad-hoc fashion, which means that the locations of the sensors are not known a priori [1]. Localization is necessary to provide a physical context to sensor readings for services such as intrusion detection, inventory and supply chain management. It is also a fundamental task for sensor network services such as geographic routing and coverage area management [1, 2]. Over the last few decades, localization technologies have undergone significant progress and they now play a crucial role for many location- and context-aware services and applications such as navigation, robotics, patient monitoring and emergency response systems.

Localization algorithms can be classified into either range-based or range-free. Range-based localization (like GPS and some forms of cellular-based positioning) can have very high accuracy by taking measurements of a signal at the cost of computational and implementation complexity. In contrast, range-free localization algorithms (such as simple cell-based localization) can provide a less accurate position (but perhaps "good enough" for the specific purpose) with a much more simple implementation. Additionally, the physical environment can have a great impact on the performance of a chosen localization algorithm. For example, while global positioning system (GPS) has been the primary localization approach for outdoor environments, indoor environments (and all other GPS-denied areas) face severe challenges such as the limited accuracy of techniques like cellular-based positioning [2] and radio propagation characteristics that can differ significantly from outdoor environments [3]. Therefore, as one of the most challenging topics in localization, indoor localization has attracted the attention of many researchers both in industry and academia.

In recent years, a variety of novel approaches have been presented, including positioning based on FM signaling [4], Wi-Fi trilateration [5] and low energy Bluetooth beaconing (e.g., iBeacons) [6]. Most such techniques rely on the received signal strength indicator (RSSI) as the main parameter to extract distance information with acceptable accuracy [7]. Infrared-based indoor localization [8], signal fingerprint-based localization [9] and image-based indoor localization [10] are examples of localization that do not rely on RSSI or other similar signal or link measurement for distance determination. However, these methods typically introduce higher costs and complexity and may not be as readily available.

Availability, cost, reliability and accuracy of localization are the most important parameters when selecting a localization method and technology. Among existing technologies, RF-based methods based on Bluetooth and Bluetooth low energy (BLE), Wi-Fi and XBee are popular choices due to their availability (e.g., BLE is available on most modern smart devices), low power consumption (particularly BLE and XBee) and low cost. Although RF-based methods have several advantages for localization purposes, they also have a significant shortcoming in indoor environments, i.e., prior work has shown that RSSI is not a reliable metric and that it can easily be affected by the unique characteristics of the indoor environment [11]. On the other hand, timing-based ranging approaches have attracted much attention using technologies such as XBee/ZigBee [12], ultra wideband (UWB) [13] and Wi-Fi [14]. Timing methods come with their own collection of advantages and disadvantages in an ad-hoc and indoor environment. In this chapter, we investigate recent work involving in the field of RF-based localization to address the challenges of RSSI- and timing-based localization in indoor environments and then review approaches that can be used to address these challenges.

The structure of the chapter is organized as follows: Section 2 presents the basic concepts of localization and its application including a discussion of common characteristics of localization algorithms. Section 3 narrows down the localization problem to indoor localization algorithms based on RF signaling. Section 4 discusses some of the challenges associated with RF-based indoor localization. Section 5 reviews how some of these challenges are addressed in recent work and addresses future research directions to tackle the remaining challenges.

2. Introduction to localization

2.1. Overview

Before we investigate localization in an indoor environment with radio frequency devices in detail, we must first establish a solid understanding of localization. The general problem of localization is the determination of the position of an object (or person) within a specific space. This location could be within some local coordinate system or it could be a global coordinate system, such as latitude and longitude coordinates on the Earth's surface. The best-known solution to the localization problem is the global positioning system (GPS), which uses the time of arrival of signals from multiple satellites to determine where the GPS receiver is located within several meters. Moreover, companies such as Apple, Microsoft, Google and Skyhook all have methods of estimating a user's location by fusing GPS, Wi-Fi and cellular data for a multitude of purposes ranging from enabling context-aware applications to locating stolen devices. The usefulness and importance of localization are difficult to understate as is the difficulty and multitude of approaches to solving this problem. Not all localization systems are created equal, for they are implemented using a variety of technologies according to the necessities of the system in which the location is required. For example, locating a car on the road has different requirements than locating a person in a shopping mall or a drone in a building. Based on these requirements, such as high accuracy or low power consumption, a localization system can be developed either by repurposing or piggybacking on existing technology or by using an existing localization system, namely, GPS.

A common way that localization is implemented is to determine the distances between a target and a sufficient number of reference points. This process is referred to as ranging. Once these distances are known, then it is possible to approximate the location of the target geometrically through trilateration or min-max. Trilateration works by using the measured distance as the radius of a circle around a reference point. The intersection of three circles is the estimated location of the target. If the circles do not intersect at a single point then further action must be taken to improve the estimate. An example of trilateration in two dimensions is shown in **Figure 1**. The min-max method takes the measured distance between the target and the reference point and uses it to form a square with side length twice that distance with the reference point that made the measurement at the center. The target is assumed to be in the center of the rectangle formed by the intersecting reference nodes' squares. An example of min-max in two dimensions is shown in **Figure 2**. Methods of localization using trilateration or min-max belong to the group of range-based localization methods. Because they are based on geometry and they are, perhaps, the most straightforward localization algorithms and have the potential for providing highly accurate location estimates.

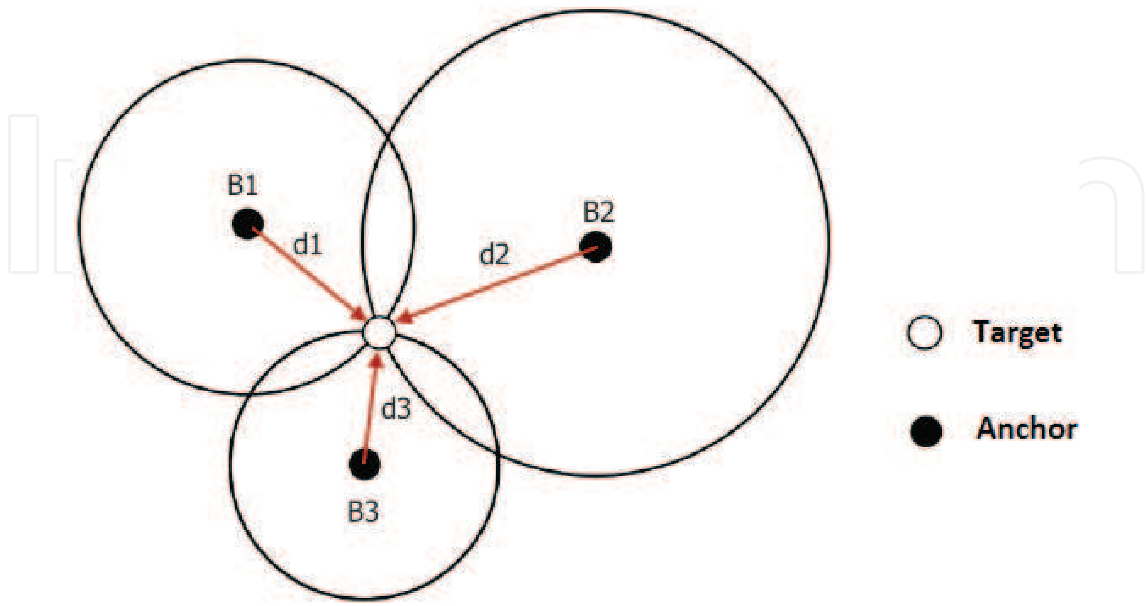

Figure 1. Trilateration technique with three reference points.

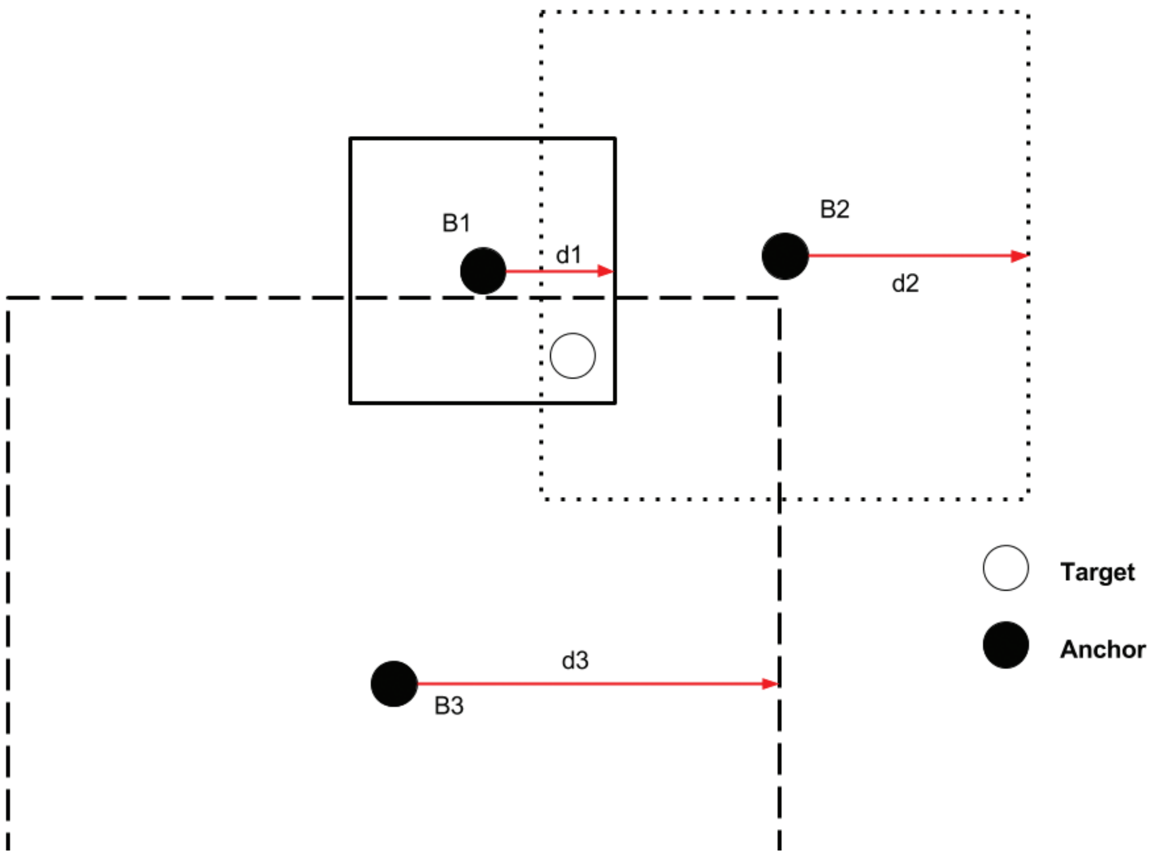

Figure 2. Min-max technique with three reference points.

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GPS is an example of such a system, because once the time of flight (ToF) of the signals from the GPS satellites to the GPS receiver is known, then it is simply a matter of multiplying the speed of the signal (the speed of light) by the time it took to travel from the satellites to the receiver (accounting for relativistic effects along the way). Note that this relies on the sender and receiver having synchronized clocks to determine the time of arrival (ToA). Time-based ranging can also be accomplished through what is called time difference of arrival (TDoA). In this method, one needs to only measure the difference in arrival time between two signals with different (known) propagation speeds. For example, one could measure the arrival time of a radio signal and that of an auditory signal and because the speed of the signals is known, it would be a simple matter to determine the distance to the target which initiated both signals. The final method of ranging relies on measuring the amount that a signal decays as it travels from (or to) a known location. That is, if we know how a signal such as a sound or a radio wave diminishes as it travels and we also know the strength of the signal to begin with, then we can determine how far the signal traveled by measuring its strength at the receiver.

It is not always necessary to determine the distance between some reference points and a target. Methods of localization that estimate a location without using ranges are called range-free. This class of localization algorithm is characterized by its use of network connectivity and geometry as well as radio characteristics to estimate the location of a target node. For example, given three anchor nodes (nodes whose locations are known) and a target that has a connection with all of them allow us to estimate the target's location by finding the centroid of the triangle created by the three anchors. There are many methods that improve this simple "find the centroid" approach as well as other methods that estimate distances based on the known anchor positions and the connectivity of the network. In general, range-based localization methods are characterized by fairly high accuracy at the cost of higher computational complexity compared to range-free localization. Additionally, some ranging methods, such as those based on timing, may require hardware that devices in a resource-constrained sensor network may not have.

Localization in an ad-hoc network further complicates the localization process by placing stronger constraints on the resources available and how they are accessed. Ad-hoc networks, whether they are mobile ad-hoc networks (MANETs), vehicular ad-hoc networks (VANETs), or wireless sensor networks (WSNs), impose some limit on the amount of information available at any particular node and come with the added complication of having to share that data in an ad-hoc manner with other nodes in the network. For localization purposes, this means that combining widespread sources of information to estimate a range or location may no longer be possible. In fact, it may not even be possible to estimate an absolute location if the network does not include any anchors. Additionally, adding in the issue of mobility, whether it is the somewhat predictable mobility of a VANET or the less predictable movement of nodes in a MANET, turns the localization problem into a tracking problem and also needs to be balanced with how and where localization computations are going to be carried out in the network.

2.2. Characteristics of localization algorithms

Aside from the primary classification as a range-based or range-free, which is largely dictated by the hardware employed, localization systems can be further distinguished by their various characteristics including their network topology, computational strategy, use of anchors and ability to handle mobility, whether it be the anchors or the targets that are mobile.

The network topology is closely associated with the method of computation and has a major impact on the localization methods available because it dictates how information is going to be passed and to whom it will be passed. For example, in a star topology, the end nodes will not be able to communicate directly (or at all) with neighboring end nodes, which means that timing-based approaches may be difficult to implement and computation will need to be carried out at the master node. However, if a mesh topology is available, then there are few restrictions (imposed by the network) on the method of localization and it opens the door to distributed computation and cooperative localization.

The availability of anchors can be a hardware constraint if a global reference frame is in use and GPS is unavailable. Anchors can also take the form of a node with a known location in an arbitrary (but consistent) frame of reference, so lacking even these data are also a possibility. The availability of an anchor could be determined by the nodes' mobility and location; for example, a node moving about within a building may become an anchor when it is in a location where it can receive a GPS signal. Anchor-based localization algorithms are those that *require* anchors to function, whereas anchor-free algorithms could operate in their absence. Range-free localization algorithms that rely on finding the centroid of the shape formed by a set of nodes can only function if the locations of the nodes are known. In contrast, the range-based localization (e.g., ToF) can localize targets without anchors.

The various forms of mobility (or lack thereof) that a localization algorithm can handle are a characteristic that may be imposed by the hardware on the nodes or it may simply be an assumption made by the designers. For example, the computational burden than can be handled by sensors in a WSN may be severely limited, so the design of an algorithm that can handle precise tracking on such hardware would be infeasible. Similarly, the algorithm designers may assume that the targets to be localized are generally static or that their movements are fairly predictable.

In addition to these characteristics, considerations must be made regarding the impact of the localization algorithm on the normal network communication and the environment in which a localization system is to be deployed. The former consideration is one that is more important with regard to optimization, so it will not be discussed here. The latter is a point that will be considered in the next section as we discuss radio frequency (RF)-based localization with a focus on its implementation indoors and the challenges arising from that.

3. RF-based indoor localization

3.1. Radio frequency devices

The radio frequency devices under consideration in this chapter are Wi-Fi, Bluetooth/BLE and XBee devices due to their wide commercial availability and frequent use in ad-hoc networks. Wi-Fi is a well-known and ubiquitous radio technology based on the IEEE 802.11 standard. It operates in the 2.4 and 5 GHz bands with three nonoverlapping channels in the former and two dozen in the latter. Bluetooth falls under the IEEE 802.15.1 standard, operates in the 2.4 GHz band and is designed for wireless communication over short ranges. Instead of focusing on replacing wired networks, Bluetooth has found great usefulness in enabling communication on a smaller scale. BLE is a version of Bluetooth aimed at reducing power consumption, which has made it possible to integrate Bluetooth into power-constrained devices. BLE has also led to the development of Bluetooth beacons, which can be used for proximity detection for the purposes of driving context-aware applications such as navigation or advertisements in shopping malls. Finally, there are XBee radios that are designed for low data rate communication in personal area networks. They also operate in the 2.4 GHz band, have low bandwidth and are widely used for home automation and Internet of Things (IoT) applications. Since all of these forms of radios operate in similar frequency bands, they can and will interfere with each other; moreover, they all experience similar behavior with respect to radio wave propagation. With this in mind, there are a variety of range-based and range-free localization methods that can be implemented with all of these radios; however, there are some methods that may be better suited to one radio than another.

3.2. Range-based localization

As introduced above, range-based localization methods are used for triangulation, trilateration, or min-max. The go-to method of ranging, due to its simplicity, is RSS ranging, which relies on the notion that the strength of a radio signal decays in a reliable and easily calculable way. One common approach is to assume that the antenna is isotropic and then make use of a path loss model to solve for the distance given the power of the signal at the source and at some unknown point. Other approaches include developing different path loss models as in Refs. [15, 16] and improving the estimated distances or locations through the use of maximum-likelihood estimation [17] or a Kalman filter [18]. Almost all of these methods of RSS ranging involve some sort of calibration (solving for environmental characterization values, calculating a path loss model, etc.) to be effective.

Another common form of ranging is to calculate the ToF of the radio signal from the sender to the receiver. Since the speed of the radio signal is the speed of light, the distance can be calculated readily. The difficulty lies in how to precisely measure ToF because the processing delay between the arrival of the signal at the radio and when these data are read at the application layer is significant and can greatly overshadow the actual signal propagation time. Rather than perform one-way ranging (OWR), where both nodes must have clocks that are synchronized, another method is to perform two-way ranging (TWR), where a message in not only sent from one node to the other, but the other node also responds with an acknowledgment. TWR is helpful because it helps to account for the processing times on either end and also does not require that the two have synchronized clocks. One can go even further and perform symmetric double-sided TWR (SDS-TWR) in which the TWR procedure is run through twice starting once at each node. This method can help with issues such as clock drift [19], which are not addressed by TWR. A final method of ToF ranging (described in Ref. [14]) leverages the ability to analyze channel characteristics combined with communication across many channels to determine ToF. The key to this method is to change finding the ToF into an application of the Chinese Remainder Theorem by analyzing the phase of the arriving signal across many channels of communication. One drawback of this last method is that it requires both the hardware and software to support such an analysis of the arriving signal, which may not be the case for a lot of consumer radio products.

The final method of radio frequency ranging is ranging in the general sense of measuring something between a reference node and a target node. Determining the angle of arrival (AoA) is a ranging method in which the angle between a reference node and an unknown node in the former's frame of reference is determined. There are two ways that this has been accomplished in the literature. The first method is to use an antenna array so that the time difference of arrival at each of the antennas in the array of the signal can be used to calculate the AoA of the signal. The second approach is referred to as synthetic aperture radar (SAR) and entails moving an antenna at a predetermined speed in a predetermined direction (for example, rotation about an axis). Using the time difference of arrival at the antenna at different points in its trajectory, the direction of the signal can be determined. With additional sensors that can account for the movement of the node, SAR can be accomplished across an unknown trajectory as well as mentioned in Ref. [20].

3.3. Range-free localization

The accuracy of range-free localization methods is typically less than that of the range-based methods; however, these methods have the advantage of simplified implementation and hardware requirements. Additionally, it is not always necessary to calculate an exact location, so range-free localization displays varying levels of accuracy and complexity, so that the right tool can be chosen for the job.

One of the most accurate forms of range-free localization is called fingerprinting and relies on RSS measurements to develop a radio map of a location. Rather than attempt to draw a relationship between the RSS measurements and the distance between the unknown and known nodes, the RSS measurements at many known locations are stored in a database during a configuration phase. Later, a new node that enters the mapped area can get its location by having its signal strength readings compared against the database.

There are many methods that revolve around the use of network connectivity information in addition to the known location of a set of nodes. With this information, the centroid of the triangle formed by three nodes with known locations is used as the location estimate of a node to which all three are connected. There are a variety of implementations of the centroid method that differ, largely, by the geometry they wish to exploit. Another method of localization, which can be used in a multihop network, is DV-Hop, or distance vector hop [21], range-free localization. This method piggybacks on the distance vector routing algorithm with the knowledge of some of the node locations to estimate the length of a hop. The hop length estimate is then used to estimate the distances from the nodes with known locations to the target nodes. The final method of range-free localization addressed here is a simple proximity-based localization system in which connectivity to a reference node is assumed to mean that the target is located in the same place. If the signal range of the reference node can be controlled, then this method can be useful for room-level localization.

4. Challenges of RF-based indoor localization

4.1. Evaluation parameters

In order to study the challenges of the localization methods and evaluate their performance, we first need to present some metrics and concepts, which define their constraints and limitations.

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(i) Localization accuracy: The localization accuracy is one of the most crucial parameters depending on the application of localization. For example, in safety applications in vehicular environments for pedestrian protection from accidents, the highest localization accuracy is desired (submeter accuracy). For less sensitive applications, lower accuracy coarse ranging (i.e., immediate, near and far region) is acceptable and for GPS-based localization, an accuracy of a few meters can be sufficient. The localization strategy, network structure, number of beacons and the devices' capabilities and technologies are other parameters that can impact the localization accuracy.

(ii) Localization reliability: Another important aspect of localization algorithms is the reliability of the methods, i.e., how consistent a localization method can be in different situations. Environment, the mobility of devices and objects in the network and type of technology are a few aspects that can impact the reliability of the localization method. Specifically, in RF-based localization based on analysis of RSSI to extract proximity information, the susceptibility of RSSI to multipath and shadowing caused by environmental changes is the main challenge to reliability (and accuracy). We will explore this further in the next section.

(iii) Power requirements: Networks (especially sensor networks) can have strict power requirements, which can impact localization performance. Two clear ways that power requirements impact localization are in the computational complexity of the localization algorithm chosen and the communication technology utilized. In the latter case, strict power requirements may push one to consider using BLE or XBee rather than Wi-Fi.

(iv) Availability/cost: For practical implementations of localization algorithms, cost and availability of the technologies and devices are the two essential factors. For example, BLE is one of the most popular and available technologies in smart devices and can easily be used for many localization purposes.

4.2. Challenges

One of the main shortcomings of RSSI-based localization (such as Bluetooth-based localization) in indoor environments is that RSSI measurements only provide a rough estimate of the distance between a transmitter and a receiver. In realistic environments, increasing the distance between the transmitter and the receiver does not necessarily decrease the signal strength (especially indoors where signals are often reflected multiple times). Another important point to consider is that even for a constant distance between the devices, the RSSI values can fluctuate very erratically over time. Based on prior work [22] and our own experiments, we can summarize some characteristics of using RSSI for ranging. The following experiments were carried out in a hallway that measures 2.41 m wide × 2.34 m high. The walls are concrete and there are multiple metal doors along them (which help to ensure the presence of multipath). In all cases, a node (either a receiver or transmitter) was affixed to the bottom of an EXIT so that the node was 2.13 m off of the ground while the other node was either carried or set on the ground for each measurement. For BLE experiments, we used Estimote beacons, and, in order to collect the BLE data (RSSI), we developed an application for smart phones using the Estimote SDK. Wi-Fi data were collected using Raspberry Pi 2B (RPi) where the RPis are used for both transmitter and receiver. We wrote some Python code to configure the RPi as a transmitter and set the transmission parameters such as transmission channel, transmission rate, etc. On the receiver side, a Python script was written to scan the channels and record the RSSI. Finally, XBee data were collected through the use of Digi

XBee S2 radio modules with a 2 mW wire antenna and software running on a laptop that uses a remote AT command to get the RSSI of the last received packet. A single RSSI measurement as reported below is actually the median of five such RSSI request values, which provides a rough filtering of outliers. Care was taken to ensure that there were no obstacles between transmitter and receiver for all data collected. That is, there was always a line of sight path between the two nodes.

In stationary cases (i.e., no device mobility and the distance between transmitter and receiver is fixed), RSSI values can fluctuate significantly between adjacent beacons, as shown in **Figures 3–5**. The BLE fluctuation data in **Figure 3** were collected at a distance of 8 m and transmit power of 4 dBm. In **Figure 3**, the RSSI measurements vary by as much as 29 dB over a 45 s period and in **Figure 4**, maximum fluctuations of 10 dB can be observed for XBee radios. The XBee fluctuation data were collected at the same distance and transmit power as the BLE experiment. Finally, **Figure 5** presents the RSSI measurements from Wi-Fi at a distance of 8 m with transmission power of 4 dBm. As can be observed, Wi-Fi shows more stable RSSI behavior with less fluctuation (e.g., less than 10 dBm).

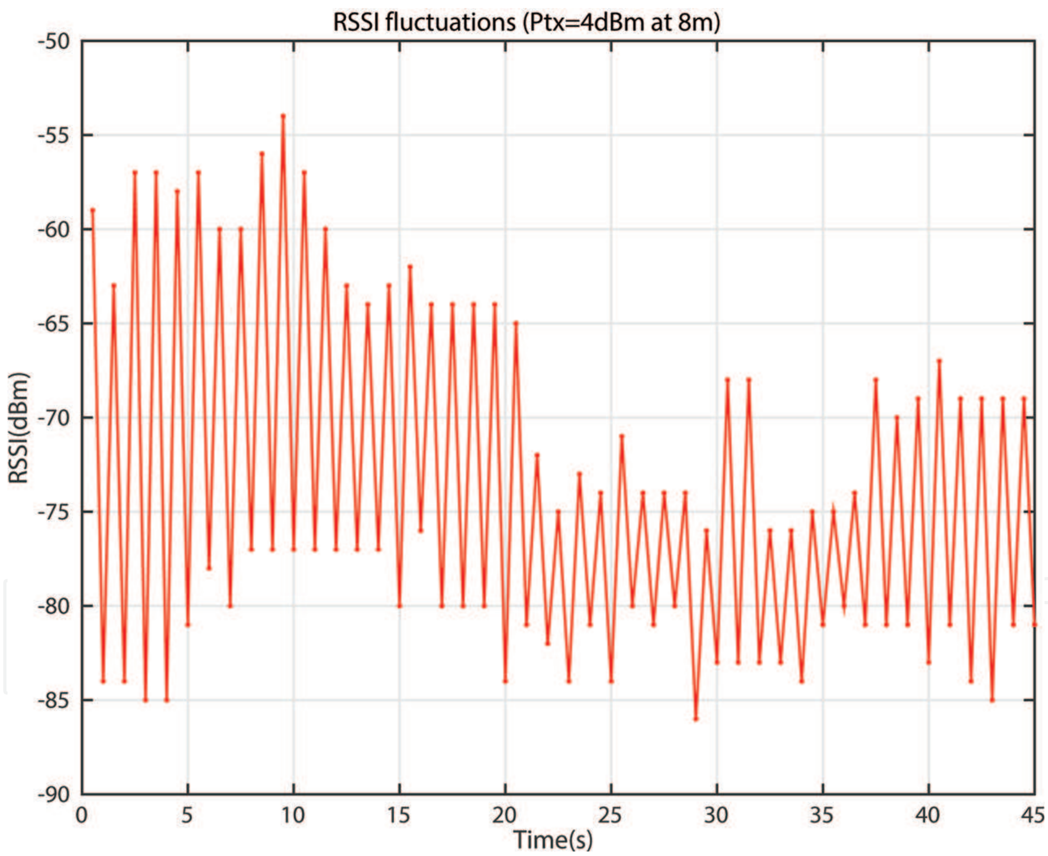

Figure 3. BLE RSSI fluctuations in an indoor environment.

These fluctuations are to be expected because all the walls, doors and floor serve to reflect the signal, which results in many copies of the same packet arriving at the transmitter with varying signal strengths. XBee would appear to be a good choice for communication in the presence of multipath effects due to its lower RSSI fluctuations, but the importance of this metric needs to be balanced with the ability to accurately and reliably relate RSSI to distance. The RSSI value is expected to decrease with increasing distances, but in practice, this relationship is not reliable. As shown in **Figure 6**, the average RSSI does not necessarily decrease as distance increases for BLE, Wi-Fi and XBee (now transmitting at 5 dBm). Note that for BLE, the data were collected while walking away from the EXIT-sign-affixed node at a rate of 0.5 m/s. In particular, for BLE, the average RSSI at a distance of 10 m is greater than the RSSI at a distance of 6 m. A similar behavior can be observed for Wi-Fi signals in **Figure 6**. We note that

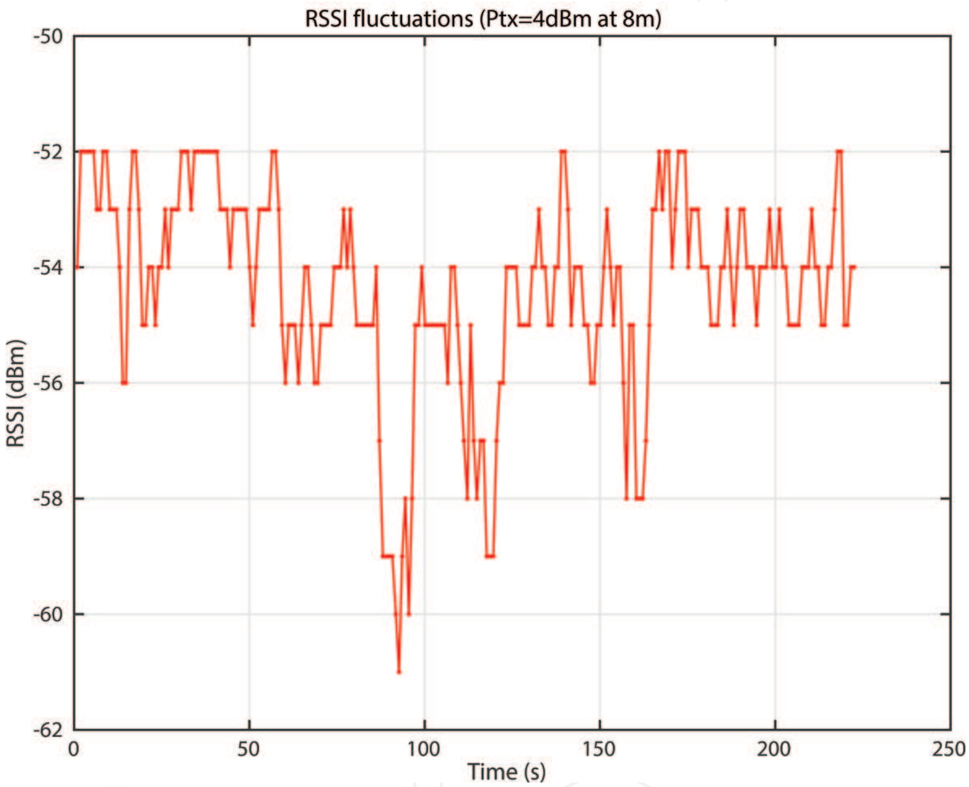

Figure 4. XBee RSSI fluctuations in an indoor environment.

if the RSSI is not averaged then fluctuations such as those illustrated in **Figures 3** and **4** can have a much greater impact on the RSSI-distance trend.

The measured RSSI values typically differ from the expected relationship between signal strength and distance. We performed experiments to show this observation for BLE, Wi-Fi and XBee. In **Figure 7**, we compare the measured RSSI with the mathematical relation between RSSI and distance for BLE presented in Eq. (1) as a function of transmission power, distance (d) and path exponent (n):

$$\mathrm{RSSI} = -(10n\log(d) - A) \tag{1}$$

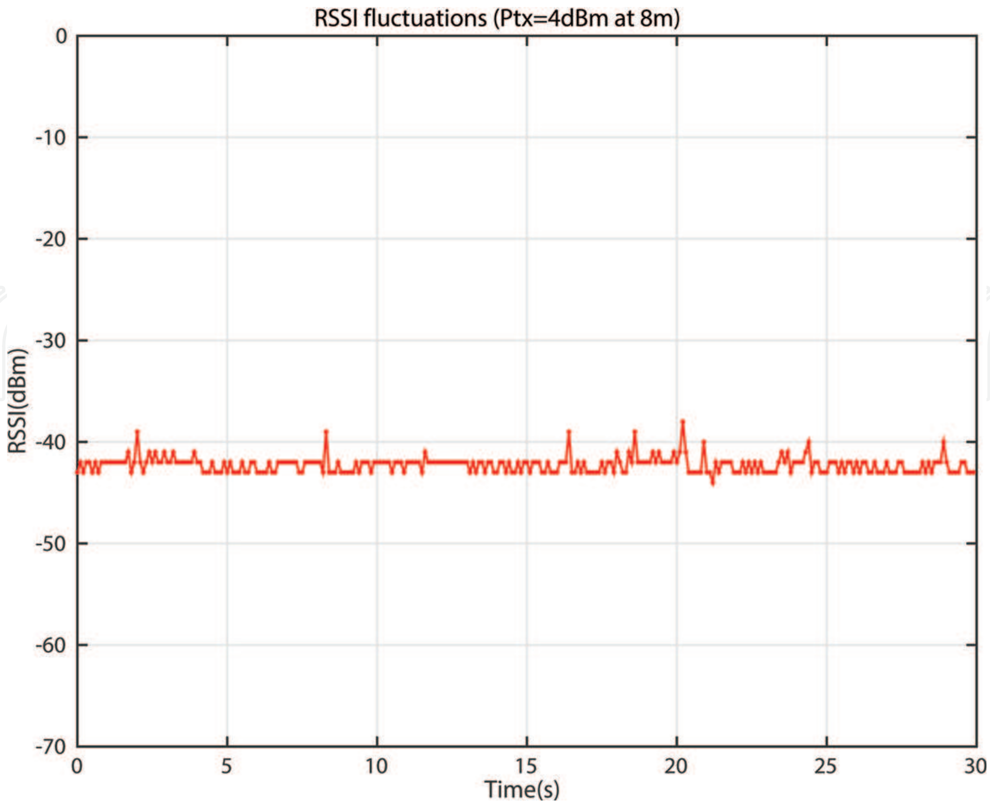

Figure 5. Wi-Fi RSSI fluctuations in an indoor environment.

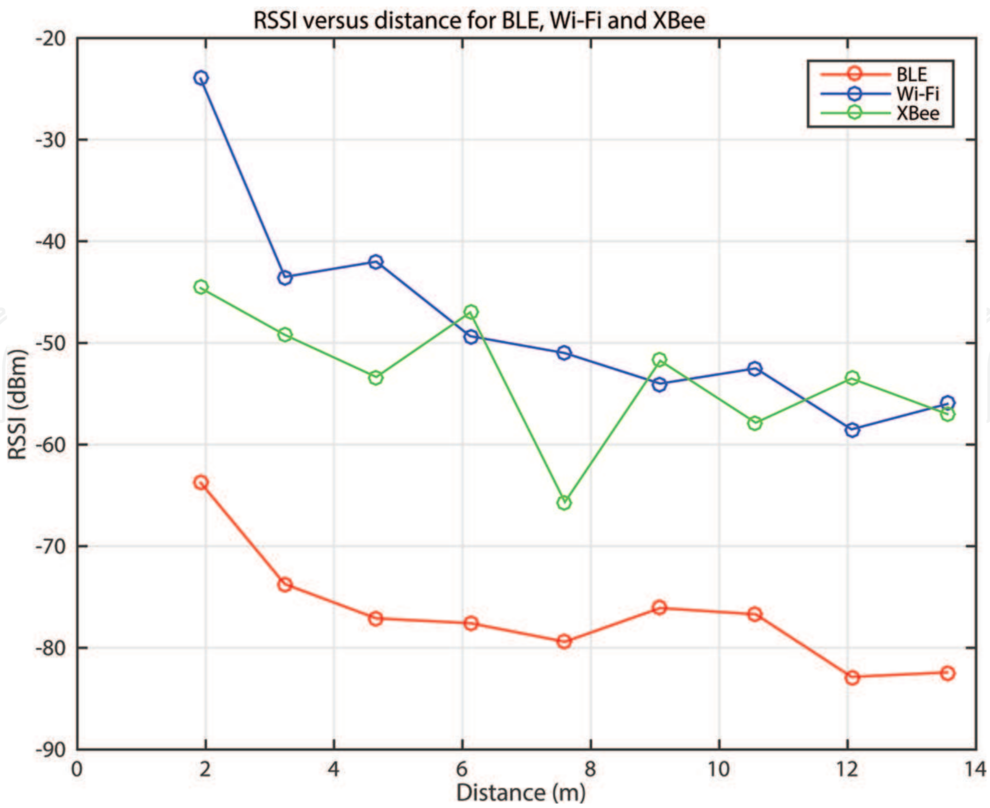

Figure 6. RSSI versus distance for BLE, Wi-Fi and XBee.

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In Eq. (1), A is the measured power, which is the expected RSSI value at a distance of 1 m to the BLE beacon. The measured RSSI is a function of transmission power. We performed the same experiment with Wi-Fi to investigate the relation between Wi-Fi RSSI and distance. **Figure 8** shows the comparison of the average of RSSI at different distances with the analytical equation presented in Eq. (2). As can be seen in this equation, the relation between RSSI and distance is a function of frequency f and RSSI.

$$\text{Distance} = 10^{\left(\frac{27.55-(20\log(f))+\text{RSSI}}{20}\right)} \tag{2}$$

Figure 9 shows the relation between RSSI and distance for XBee in the same environment using the same equation as BLE (using different parameters). This figure also indirectly illustrates the sensitivity of radio frequency communication to the environment because here the transmitter was held 1 m off the ground rather than sitting on the ground as shown in **Figure 6** and the relation is much closer to a log relationship between distance and RSSI than the data in **Figure 6**.

The effect of an indoor environment on signal propagation is the primary reason for these data not matching with their respective theoretical model. Any particular packet (or set of packets) may be influenced by multipath despite averaging of results. Additionally, the transmit power, receiver sensitivity and antenna orientation all play a role in influencing RSSI and cause it to no longer follow the theoretical relationship. It is also important to note that the interference from other devices in 2.4 GHz band could have had a hand in driving the measured RSSI away from the expected values.

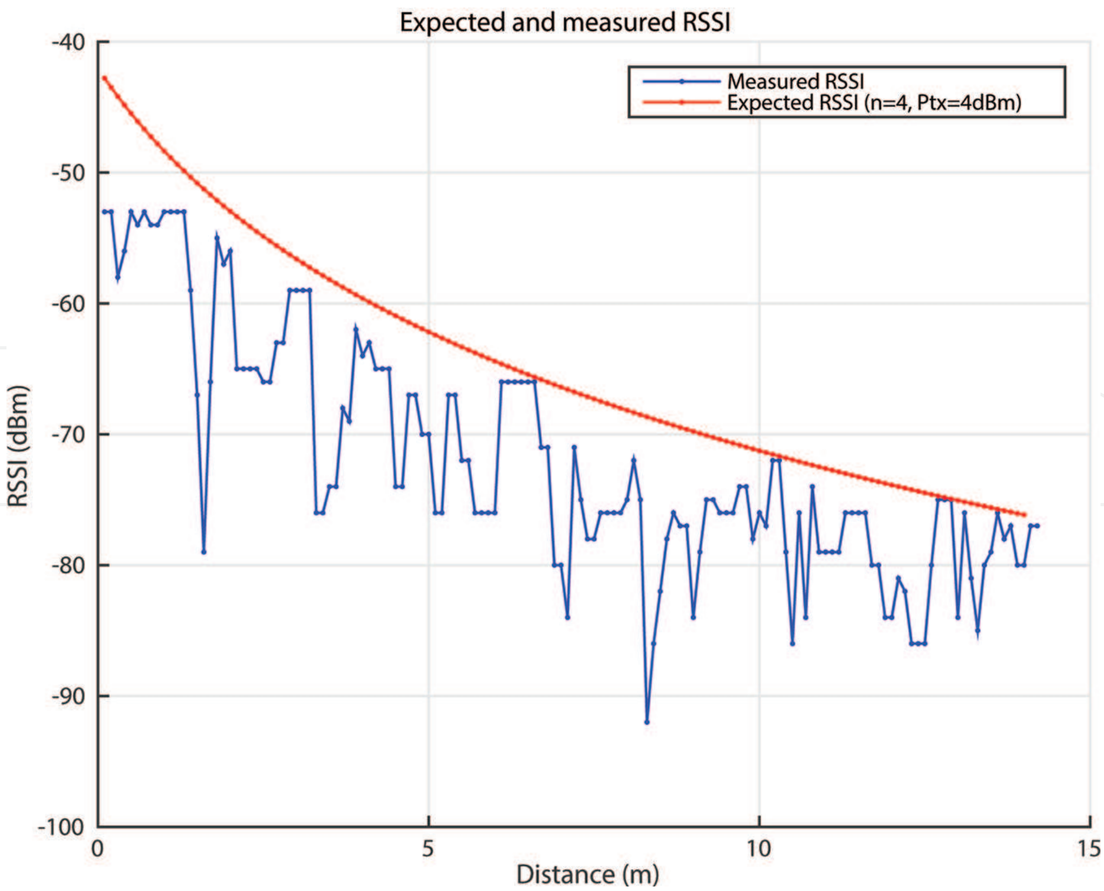

Figure 7. RSSI versus distance for BLE (analytical model and measurements).

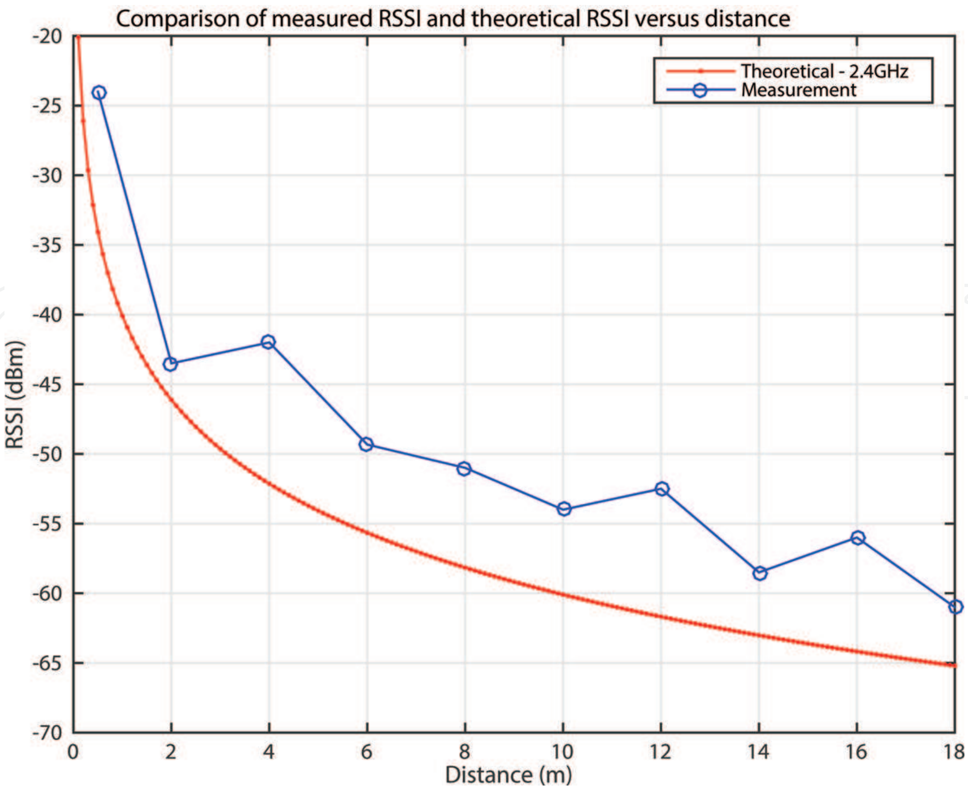

Figure 8. Average RSSI versus distance for Wi-Fi-2.4 GHz (analytical model and measurements).

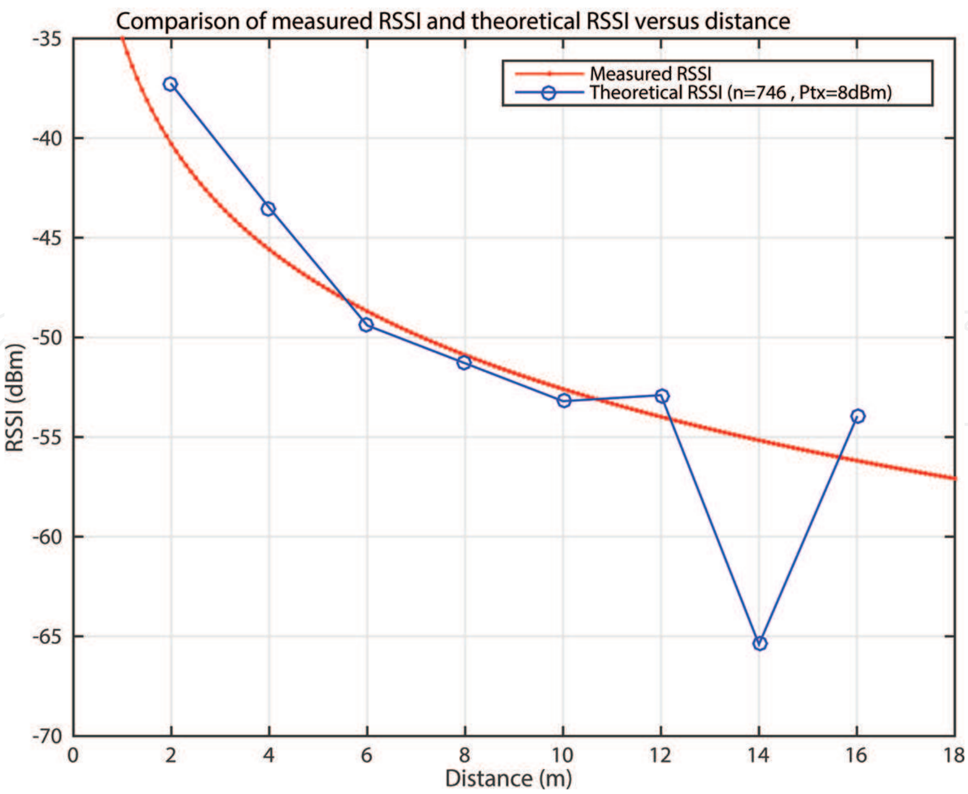

Figure 9. Average RSSI versus distance for XBee radio (analytical model and measurements).

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The differences in ranging accuracy are difficult to compare between the different types of radio frequency devices because RSSI is not, by any means, a strictly defined value. Beyond the fact that RSSI is an 8-bit integer representing the strength of the signal, there is little specification as to its implementation. This means that RSSI implementations can differ between vendors of different radio frequency devices and even the same type of radio frequency device.

Finally, as mentioned earlier, the RSSI value fluctuates even for fixed distances between transmitter and receiver. However, these fluctuations vary based on distance, i.e., the larger the distance between transmitter and receiver, the larger the variations observed in the measured RSSI values, as shown in **Table 1**. As shown in **Table 1**, the errors become significantly larger when the receiver is further from a transmitter for BLE beaconing.

Distance (m)	Std. dev. (dBm)	Avg. RSSI (dBm)
3.23	3.76	–63.28
4.65	5.43	–69.60
6.11	4.90	–67.44
7.59	4.64	–65.42
9.07	3.55	–68.57
10.56	6.16	–71.44
12.05	7.89	–74.42
13.55	6.57	–74.28
15.04	7.83	–77.36

Table 1. Average RSSI and standard deviation for BLE.

5. Possible approaches to address the RF-based localization challenges in indoor environments

In the previous section, we reviewed the main challenges of RF-based localization. The main source of these challenges is the structure of indoor environments, which causes multipath effects, heavy shadowing, noise interference and nonline of sight (NLOS) conditions. Additionally, indoor environments must contend with the mobility of obstacles, which has a far greater effect on localization than in an outdoor environment. In the following section, we review various efforts to address these challenges.

5.1. Leveraging channel state information

In recent years, Wi-Fi chipmakers have made channel state information (CSI) per subcarrier (and per antenna) available on their chips. Using a CSI extraction tool, the authors [14, 20, 23] illustrate the use of the channel subcarrier information to achieve decimeter level localization accuracy. In particular, Kotaru et al. [23] use multiple antennas and CSI to calculate the angle of arrival (AoA) and uses a rough estimate of the ToF to provide resilience against multipath effects. Localization is accomplished using a combination of RSSI and AoA for ranging at each anchor. Vasisht et al. [14], as mentioned earlier, use the CSI to calculate the ToF by taking measurements at many different frequencies. Finally, in [20], the authors present Ubicarse, which combines CSI with the gyroscopes in a tablet to realize a synthetic aperture radar (SAR) to carry out localization. The ability to access and analyze this rich source of radio information is incredibly helpful in improving RF-based ranging in an indoor environment and could easily see deployment in an ad-hoc network as long as the hardware and software required to utilize CSI fit within the constraints of the network.

5.2. Calibration

Another technique for improving the reliability of RSSI is using calibration or adding an adjustment factor based on the network parameters such as network dimension, transmission power and number of beacons. The main idea behind the calibration technique is to use the relationship between RSSI and the actual distance between several nodes (usually the anchor nodes with known positions) and utilize it as an offset value to adjust the RSSI for distance estimation. In Ref. [24], the authors attempt to calibrate the RSSI-distance model by using least squares to adjust the reference power at 1 m as well as the path loss exponent. By adaptively calibrating the system, it achieves a lower error and better reliability than methods that only calibrate manually during setup or after a major change. Calibration in this way keeps the range estimation from deteriorating when the environment changes.

As an example of calibration, we implemented a network with three Bluetooth beacons at known locations. We measured the RSSI values at different distances and compare it with the analytical equation as presented in **Figure 7**. To calibrate the ranging measurements, the RSSI was measured between two different pairs of beacons such that the distance separating the pairs was sufficiently dissimilar. Between these new RSSI-distance points, we interpolate a line, which is used to adjust the RSSI measurements. **Figure 10** shows the RSSI-distance graph after using the calibration.

Also, **Figure 11** shows the comparison of the distance error with and without calibration, showing that the calibration can improve the distance estimation error. However, there are still some large peaks in the error graph which illustrate that even with the use of calibration, RSSI is not a completely reliable parameter for distance estimation.

5.3. Adaptive beaconing

Adaptive beaconing is another approach that can be useful for different situations in the network by changing the transmission rate and/or transmission power of the beacons.

Adaptive transmission rate depends on the application of localization. For some applications, such as mobile device tracking and navigation systems, higher transmission rates are needed to keep track of a mobile device. A serious challenge for such systems with high transmission rate is the high packet collision and delay that can affect the localization performance significantly.

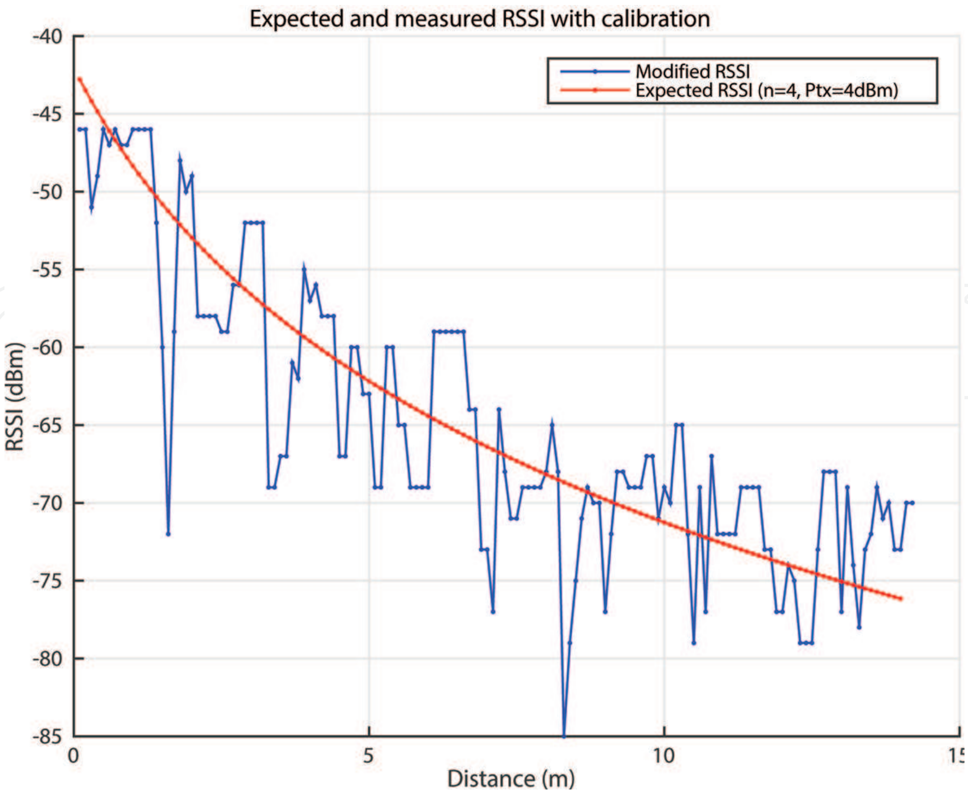

Figure 10. The measured RSSI after calibration.

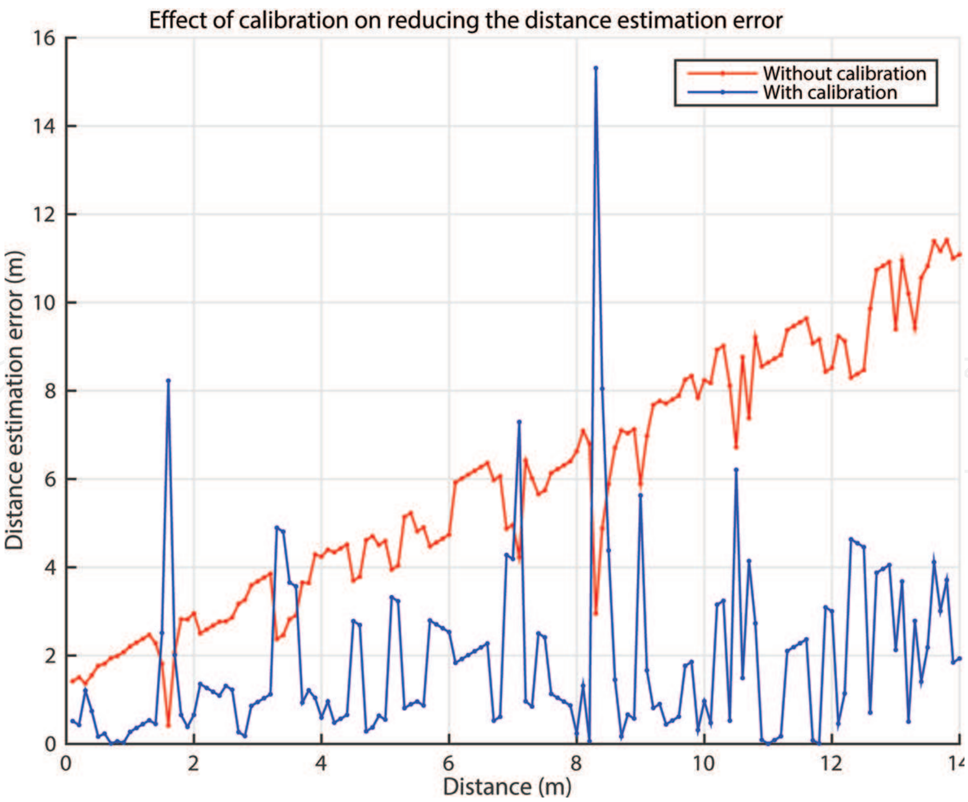

Figure 11. Comparison between distance errors when using the calibration function.

Adaptive transmission power, or multirange beaconing, is an approach that can be utilized to improve the distance estimation for localization purposes. In Ref. [25], the effect of transmission power and number of anchors on accuracy of localization and connectivity of nodes is investigated. In order to evaluate this approach, we ran some experiments by choosing five transmission power levels (–30, –20, –12, –4 and 4 dBm) and measuring the distance error for each transmission power. The average distance error over all transmission powers was also recorded. The measurements were conducted in separate scenarios to avoid any interference. **Figure 12** shows the comparison of the distance error estimation for our measurements. As indicated that with increasing distance, the error increases for each particular transmission power. More importantly, the distance estimation error changes for different transmission powers. Low transmission power can provide very high accuracy distance estimations over short distances from the beacon while high transmission powers are better for distance estimation of greater distances. This illustrates that adapting the transmission power to the distance can provide higher accuracy distance estimation than using a single transmission power alone (or averaging the results of all the transmission powers).

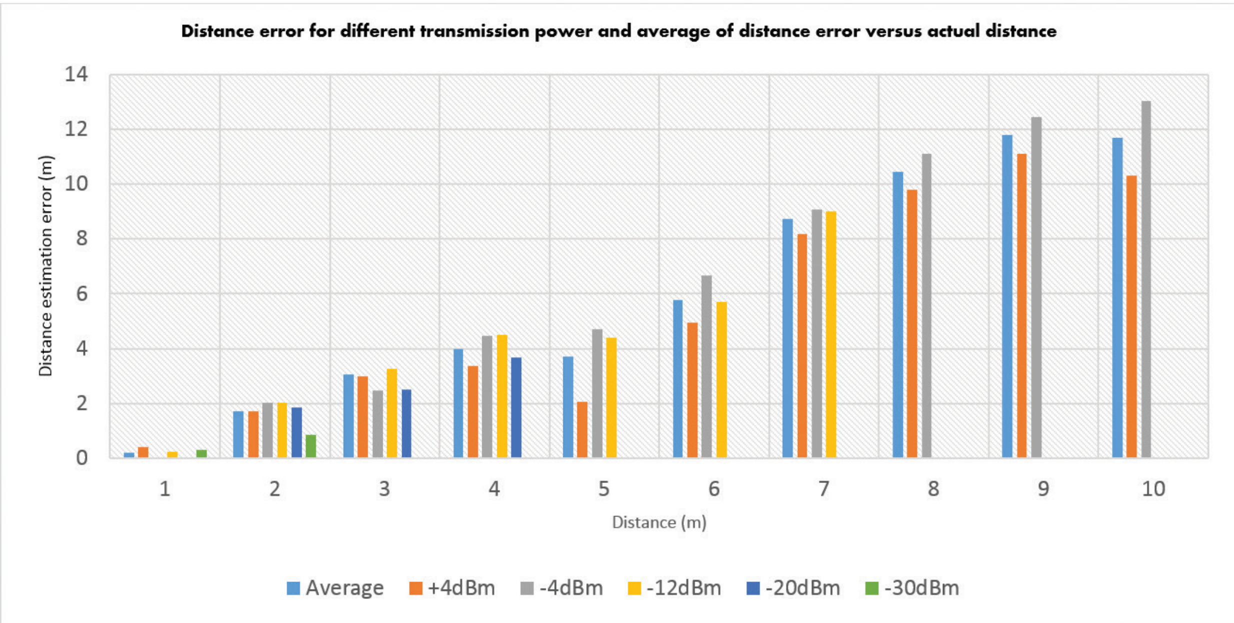

Figure 12. Effect of transmission power on distance estimation error.

5.4. Combination of RF signaling

Another approach for improving the distance estimation and reliability of RSSI is combining different RF-based communication technologies. Recently, Bluetooth-based localization has attracted a lot of attention because of its availability and cost, but many of the efforts rely on unreliable RSSI for proximity extraction in indoor environments. To address this problem, several prior efforts combined Bluetooth beaconing with other technologies such as Wi-Fi [26], Zigbee [27] and RFID [28] to further improve the localization accuracy. Although combining these technologies can improve the localization accuracy, it introduces other challenges such as availability, complexity, or implementation problems that make them less practical solutions.

5.5. Fusing additional sensor data

With the availability of multiple sensors on nodes in some ad-hoc networks, one approach to improve localization estimates is to somehow fuse data from these other sources to, hopefully, cover up some of the shortcomings of RF ranging. For example, ToA and RSSI ranging using anchors can be combined with dead reckoning to improve localization as demonstrated in Refs. [29, 30]. In the former, the authors used two-way time of arrival (TOA) for localization of vehicles in a vehicular network. They assume the existence of a road side unit (RSU) where the vehicles use two-way communication with the RSU and a partial dead reckoning method to determine the position of vehicles in GPS-denied areas. In the latter work, pedestrian dead reckoning location estimates are combined with RSSI localization estimates through the use of an extended Kalman filter (EKF) with some success.

5.6. Cooperative localization

In some network layouts, it is not always possible for every node to communicate with the anchors nodes (if there are any). In such a case, nodes must work together through cooperative localization to figure out where they are all located. Cooperative localization is similar to relative localization but also includes the possibility of some anchors nodes somewhere in the network as well as the potential for fusing additional data from onboard sensors (available in a vehicle or a smartphone) to help localize a node. In [31], pedestrian dead reckoning (PDR) with a smartphone is combined with Wi-Fi RSSI ranging where RSSI is used to determine when two smartphones are near to each other. In this way, the RSSI ranging can help correct heading inaccuracies from PDR. The path that a person takes is abstracted as a series of lines and joints where the RSSI ranging allows for the correction of the joint angles. In Ref. [32], relative localization through ranging is combined with the network topology and graph theory concepts to develop distributed cooperative localization algorithms that can greatly reduced computational complexity and provide resilience to noisy internode measurements. Cooperative localization has great potential in robotics, MANETs and VANETs.

6. Discussion and conclusion

In general, localization in any network can be improved through the exploitation of additional information whether it is from multiple sensors, extra data from the radio, or additional location estimates from neighbors. The goal is to leverage data that is already available so as to not increase the cost or resource requirements of nodes in an ad-hoc network. However, the solutions presented to the above indoor radio frequency localization issues are still not the end of the road for indoor localization or localization in GPS-denied locations. No single solution is going to work everywhere because of constraints on the network, e.g., the availability of particular hardware to carry out localization. Additionally, some networks may not have the luxury of dedicated beacons or anchors, or they may be located in a highly dynamic environment such that RSSI ranging becomes even more troublesome than usual. Finally, on top of the issues of accuracy and cost, there is the issue of the impact of the localization scheme on the performance of the network. The use of passive beacons or active ranging messages could, in the best case, mildly interfere with communication or, at worst, impose a severe restriction on the communication capabilities of the network. The difficulty and importance of indoor localization will ensure that creative and innovative solutions will continue to be sought by those hoping to develop the indoor equivalent of GPS. Whether a single method will satisfy the requirements and constraints of the many disparate networks in use today remains to be seen.

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