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A Comparison of Wireless Standards in IoT for Indoor Localization Using LoPy

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ABSTRACT There are surplus applications in modern smart cities where localization of indoor environments is critical ranging from surveillance and trailing in smart structures to the localized wireless distribution of advertising content in shopping malls. These applications are only successful if a robust and cost-effective real-time system is developed for precise localization. Another aspect considered for indoor localization is power consumption. Recent wireless standards such as Bluetooth Low Energy (BLE) and LoRa consume less power which makes them a perfect candidate for indoor localization. This work aims to carry out an experimental evaluation which would help to decide which wireless standard i.e., Wi-Fi, Bluetooth Low Energy (BLE), and LoRa are most suitable for indoor localization. Experiments are carried out using trilateration in three multiple environments. RSSI is used to calculate the coordinates of a sensor node. Results obtained from the experiment show that Wi-Fi is most accurate with an average error of 0.54 m. LoRa is second most accurate with an average error of 0.62 m and BLE is the least accurate with an average error of 0.82 m. These results can be used to decide which wireless standard is best suited for indoor localization.

INDEX TERMS Indoor localization accuracy, Internet of Things, RSSI, Wi-Fi, Bluetooth low energy, LoRaWAN.

I. INTRODUCTION

Nowadays Internet of Things (IoT) are using cheaper, low energy devices such as Bluetooth Low Energy (BLE) which are being used to communicate with the IoT and provide much-needed information for the users to control the overall physical world which seemed impossible in the past [1], [2]. Different techniques in IoT are used for location awareness of the sensor nodes especially in an indoor environment where it is difficult to track the position of the node. Without knowing the location, the data obtained from a specific sensor node is futile. Therefore in order to successfully utilize the resources it is important to determine the location [3]–[5]. For this purpose, a technique called indoor localization is used. Notable applications for indoor localization include guiding the people in a. It can also be used for tracking of patients in a hospital [6], [7]. Another application would be to locate the position of the alarm if there is a fire emergency in a building [8]. A lot of work is still being done on indoor localization for improving accuracy. Global Positioning System (GPS) is considered a promising technique for outdoor localization but due to the absence of Line of Sight (LoS) between transmitter and receiver, it cannot be used indoors.

This technique is used because the Global Positioning System (GPS) is not able to determine the position of the object being tracked inside buildings. Indoor localization is used to track nodes/objects in those environments in which GPS does not operate and is often set up in outdoor environments and needs more energy to operate [9]. Moreover, GPS is only accurate up to 5 m [10] and needs a line of sight between the transmitter and the receiver to function properly. However this is not the case for indoor localization as in these environments an accuracy of less than a meter is needed for properly determining the position [11]–[13].

A biggest constraint that is observed in IoT based devices is their limited size and limited storing capacity as well as

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low processing power, so any scheme that is used to carry out for localization should take into account all these factors. Additionally indoor localization also faces issues related to obstacles which are not encountered outdoors. For example in a building there are different levels, walls, movable items, people and other electronic and wireless devices such as PCs, luminous lights, Wi-Fi, Bluetooth which may continuously add multi path fading effect [10], [11]. Apart from the above discussed disadvantages notable advantages of indoor localization are also present in diverse fields [14], [15]. So far a benchmark for indoor localization has not been set due to increased number of hurdles inside a building [11] and multiple schemes are used to determine the position of the node indoors.

Different wireless standards have been nominated in different research papers, in which Bluetooth Low Energy (BLE), Wi-Fi and Radio Frequency Identification (RFID) gain much attention [11]. Due to the availability of Wi-Fi networks in buildings in large quantity, it has proven to be a good agent for indoor localization. Moreover due to the advent of BLE beacons indoor localization can be carried out with inexpensive hardware [16]–[18]. Moreover, with the advancement of these wireless standards, new areas are being explored to use them for localization-based services.

A. MOTIVATION

Due to this increase, there is a growing demand in the area of location awareness especially in indoor space. For designing an accurate localization system, the selection of a suitable wireless standard is considered crucial. Most wireless standards use RSSI as a way to determine the location of a user using an indoor propagation model. RSSI of different wireless standards is affected by several indoor factors such as multipath fading due to reflection, refraction of signals from surrounding objects e.g. furniture, walls, etc, and shadowing. These uncertainties affect localization accuracy. As a consequence of localization error, unwanted behavior of a localization system may be expected. To overcome this problem, a motivation to evaluate and select a suitable wireless standard is required. In this research work, an experimental approach is used to carry out a comparison between Wi-Fi, BLE, and LoRaWAN's location accuracy based on RSSI values using Pycom's Lopy v1.0 hardware. RSSI is used because it is easily available in any wireless hardware available today. Moreover, selected hardware has the additional feature of having built-in Wi-Fi, BLE, and LoRaWAN standard and requires no additional hardware for the experimental work to be carried out. The mentioned wireless technologies were chosen due to their easy availability. Trilateration was used in the testbed and three different environments were selected with different architecture to test wireless standards under different conditions.

The rest of this paper is organized as follows: related work is described in section II. Related background is provided in section III. Description of wireless standards is given in section IV. Description of experimental setup is given in section V. Hardware and software used in this work is described in section VI. Details on experimental procedure is given in section VII and section VIII concludes the work.

II. RELATED WORK

Different approaches have been applied in the last few years to build an efficient indoor localization system. An ideal system would efficiently perform in various environments and also, would be capable of tracking different targets with negligible error. A comparative study of wireless technology would be necessary to figure out the optimal indoor localization.

In [19] BLE and Wi-Fi are compared, the technique used in the experiments is trilateration in both outdoor and indoor environments. Experiments were performed for both line of sight (LoS) and non-line of sight (NLoS) conditions, RSSI values along with lognormal attenuation model were used to determine the distance between nodes. The results suggest that BLE has outperformed Wi-Fi in indoor localization and is 27 percent more accurate.

In [20] ISM868 and Zigbee, wireless technologies are compared using a similar RSSI-based trilateration model. Experiments were performed in both outdoor and indoor environments using RSSI measurements to determine the distance between nodes. Here results suggest that both technologies are not suitable for indoor localization but Zigbee is the better of the two technologies. The hardware used for the experiment may have contributed to the error rate, a fall detector is used as the transmitter to test using ISM868 but this fall detector is not a recommended device for localization purposes and may have contributed to the high error rate.

In [21] RFID and BLE are compared for localization of objects in outdoor environments and like other papers RSSI along with the path loss model is used for localization using the trilateration model. Results concluded that BLE is better than RFID with higher accuracy of tracing and locating objects but the number of devices used was two instead of three for proper positioning.

In [22], Wi-Fi,BLE, Zigbee and LoRaWAN were compared. Here the parameters in consideration are accuracy and power consumption of different devices used to compare between different wireless technologies. Three devices were used as beacon nodes (Transmitters) while the fourth device was used as a sensor node(Receiver) to approximate the location. Results suggested that Wi-Fi is more accurate of all the technologies used with a low error rate, BLE proved to be second best and LoRaWAN which transmits at a low frequency of 915MHz had a high deviation off its transmission range when transmitting at maximum power.

In this paper we have compared the three of the most commonly used wireless solutions prevailing in indoor localization i.e. Bluetooth low energy (BLE), LoRaWAN, and Wi-Fi (IEEE 802.11n 2.4 GHz band). We measured RSSI along with path loss to approximate distance between nodes and implemented trilateration model for localization. We performed the experiments in three different environments for better analysis i.e. Lab environment with different electronic devices around, corridor and class room with chairs and tables around. Hardware used for localization is Pycom's LoPy. Reason for using this hardware is availability of Wi-Fi, BLE and LoRa on a single chip.

III. BACKGROUND

A. LOCALIZATION

The process of localization involves finding the precise location of either the sensor node or the beacon node or both nodes in a given network. In small-scale applications where the number of nodes is limited, the localization process can be carried out manually but in large-scale applications having a large number of nodes manual localization is not possible. Therefore, self-localization is used in these scenarios. In self-localization, a group of beacon (anchor) nodes identifies their position by either GPS or by placing the anchor nodes in known locations. The location of anchor nodes is used as a reference by the sensor nodes to determine their location [23]. Localization can be classified as range-based or range-free based. Most popular algorithms such as Time of Arrival (ToA), Time Difference of Arrival (TDoA), Angle of Arrival (AoA), Received Signal Strength Indicator (RSSI) are categorized under range-based algorithms. Range free algorithms include DV-HOP, Multihop APIT, Gradient, Cnetroid [24]. According to [25] ToA, TDoA and AoA provide accurate location information but require additional hardware. The setup of AoA requires a large array of antennae at each node to be able to know the exact angle of the propagated signal and requires complexity as well as increased multipath effects which make AoA unsuitable for indoor localization. ToA and TDoA use time synchronization between the access point and the receiver for localization. The setup used in ToA and TDoA requires extra hardware and cost become a major constraint. Until now the easiest way to carry out localization is the method of measuring the RSSI of the received signal. RSSI measures the signal strength of the transmitted data on the receiver.

B. RSSI AND CHANNEL MODEL

RSSI is an efficient method for range-based localization. The signal strength is inversely proportional to the power of distance. The greater the distance the smaller the value of RSSI. The relation of RSSI values and distance between the nodes is represented by the path loss model [26]

$$RSSI[dBm] = -10\eta \log_{10}(D) + \gamma \tag{1}$$

where η is the path loss exponent, D is the distance between the transmitting and the receiving device and γ is the RSSI at the reference distance which is normally taken as 1 m. The path loss model is a reliable relation to find the distance using the received RSSI values. The path loss model is chosen because it also compensates for interference parameters such as multi-path effect using the path loss exponent as it is different for each environment.

C. TRILATERATION

Trilateration is a technique in which the two-dimensional coordinates of the sensor node are determined using a point of intersection formed by the three concentric circles of each wireless standard to estimate the position of the sensor node [27]. The trilateration experiment involves three nodes which are called anchor nodes are continuously broadcasting packets. Upon receiving these packets of data by the sensor node, the RSSI values are extracted and recorded. These values are used to determine the distance between the nodes. In the trilateratio experiment, the anchor nodes are set as stationary and their coordinates are known while the sensor node whose location is to be determined is placed at geometric locations in between the anchor nodes. Coordinates of these nodes are chosen in a 2D plane. e.g. coordinates for one of the anchor nodes are chosen to be (0,0). This point is also called the "origin" and this node is referred to as a reference node. Coordinates of the other two anchor nodes are chosen with respect to the reference node. In trilateration, anchor nodes are placed in a triangular fashion. This concept is shown in Fig. 1. In the given figure the distance of sensor node from

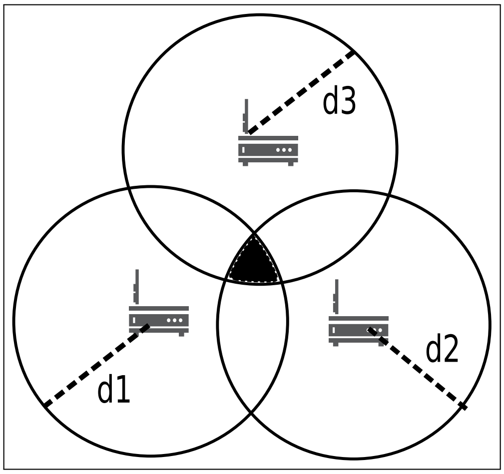

FIGURE 1. General trilateration setup.

anchor nodes 1, 2 and 3 is d_1, d_2, d_3 respectively. By using the geometric equations of circle and (1) the location of the sensor node can be estimated.

IV. WIRELESS STANDARDS

A. WI-FI

Introduced in 1997 [28], this technology is the most popular wireless technology. It operates in the 2.5 GHz band as well as the 5 GHz band. It has multiple modes i.e. IEEE 802.11 a/b/g/n. This technology is readily available in all types of the indoor environment such as office buildings, houses, educational institutions, etc. It has a greater range of about 100 m and now 1 Km [9]. A lot of work in the literature focus on using Wi-Fi for localization due to ease of availability. One example of such a localization system is Wi-Fi based fingerprinting method [29], [30]. Due to its long-range it can cover a larger area than Bluetooth which makes it a perfect candidate for commercial indoor localization systems. Moreover, Wi-Fi is more secure than Bluetooth due to its advanced encryption method. Due to enormous usage of Wi-Fi in multiple applications, there will be interference issues, as more and more devices continue to take part.

B. BLUETOOTH LOW ENERGY

BLE was introduced in 2010. This technology consumes less power and is designed for nodes and such applications that require less amount of data rate. It makes devices cost-effective [28]. BLE initiated by Bluetooth special interest group uses less amount of energy in contrast to regular Wi-Fi thus reducing its bitrate. Over the past few years, the use of BLE in various applications has significantly increased. Due to its less consumption of power, much new hardware has been introduced in IoT. This technology is perfect is considered favorable for applications where short-range transmission of a small amount of data is required. The use of BLE is not restricted to specific areas. An innumerable number of devices have been developed until now that use BLE technology such as from the field of health care to the home entertainment devices. The devices compatible with BLE can have different states. These states are *Initiator, Master, Slave, Scanner, Standby, Advertiser*. BLE is often called Bluetooth smart and is considered an ideal technology for IoT.

C. LoRaWAN

The low range wide area network can transmit data at a frequency of 915MHz. It was developed by LORA alliance [31]. The transferal of encoded data at different frequencies makes this technology secure as compared to other technologies. In LoRaWAN, since the low requency is used, this allows signals to pass through various hurdles or obstacles that might cause issues with the transmission of large wavelengths. This advantage ultimately leads to the transference of large wavelength signals to greater distances. The devices using this technology are not liable to be influenced by noise since the frequency of 915MHz exploited by Lorawan is empty. Sometimes for using LoRaWAN extra hardware (antennas and nodes) is required for communication. Lorawan requires no authentication as it uses a 915 MHz band and requires no additional license for its operation [32]. Its long-range data transmission capability makes it favorable for various projects such as those projects that use different types of sensors to deliver information (smart city projects). LoRaWAN in line of sight mode is considered efficient in long-range outdoor localization but when it comes to short-range indoor localization, it can create problems.

V. EXPERIMENTAL SETUP

In this section the methodology adapted, the description of the three environments and the hardware used are described.

A. LOCATION AND DIMENSIONS

The experiments were carried out at The University of Management and Technology, Lahore at the Department of Informatics and Systems at the following locations.

- Graduate Lab
- Corridor
- Class Room

The experimentation was carried out in between the time duration of 1700 hours and 2100 hours because a minimum amount of student strength was available during this period. The graduate lab is a 24 × 24 square feet room and was an ideal location for testing as it contained 25 to 28 computer systems as well multiple access points which would create a perfect interference environment for testing. The corridor has a 23 × 23 square feet area and was the second-best option for a noisy environment as multiple access points were available throughout the corridor. Moreover, the physical existence of the students passing frequently from the corridor and the narrow architecture created the best fit for a multipath fading environment. The third location selected was a classroom with an area of 50 × 30 square feet with 20 to 25 tables and chairs. This environment contained no wireless access points which would create a perfect noise-free environment. In all three locations, the nodes were placed at 0.76 m from the floor.

B. NODES PLACEMENT

Since RSSI values are interference susceptible, therefore to make the readings more consistent and to avoid inappropriate RSSI values, their number was increased to 100 readings per experiment whose mean was taken afterward. In each of the experiments, nine observations were considered for all environments by continuously changing the position of the sensor node. The layout of the experiment for the three locations along with the node placement is shown in Fig. 2. In the experiment, a triangle was created as shown. P1, P2, and P3 are the known position of the sensor nodes respectively. The distance between the beacon nodes was considered equal i.e 1 and 3 m.

C. NODES CONFIGURATION

To maintain fairness in the overall experiment the transmit power and the transmission time were configured to be equal for the three wireless standards. Since the transmit power for Wi-Fi and BLE was nonconfigurable and according to [33]the common value for both is +14 dBm. The LoRaMAC was configured to transmit at +14 dBm at a spreading factor of 7. The delay between transmission intervals can be configured for all the three wireless standards so a common delay was set i.e 2 seconds. The transmitters were powered up using external battery banks with an output rating of 5v 2.0A and a backup time of 11000 mAh.

VI. HARDWARE AND SOFTWARE

The hardware which was used as a building block of the experiment was Pycom's Lopy v1.0. It is built upon a powerful dual-core 32–bit microprocessor (ESP32) along with a 512 KB memory and a 4 MB external flash memory for storing code. It is Micropython enabled. It contains three communication modes i.e Wi-Fi, BLE, and LoRa. LoPy uses

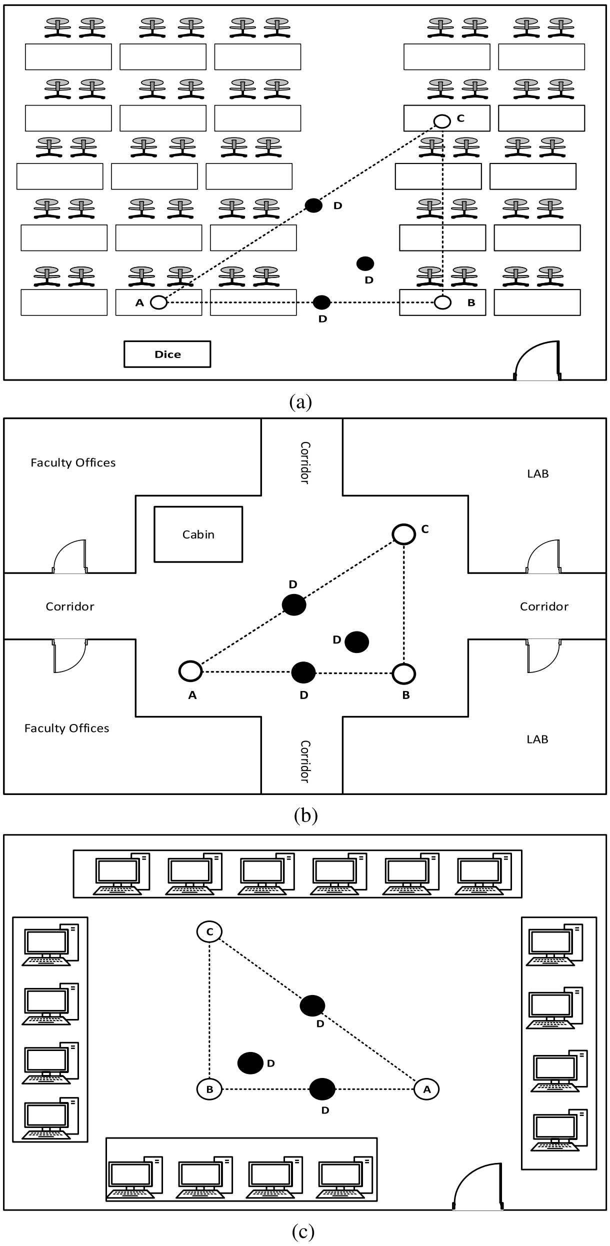

FIGURE 2. Layout for (a) Class room, (b) Corridor and (c) Graduate lab.

deep sleep mode when not in use to save power and hence it can be considered the best option in those scenarios where power is a serious issue. The ESP32 interfaces in the LoPy consist of UART, GPIO, I2C, SPI, and a micro SD card for storage purposes [34]. It takes a voltage range from 3.5 V to 5.5 V and regulates it to 3.3 V. It also has a built-in RTC of 150 kHz [33]. Fig. 3 shows a LoPy v1.0 module.

A. HARDWARE

Pycom's LoPy has built-in Wi-Fi, BLE, and LoRa. This makes LoPy a perfect candidate for applications that may require more than one wireless standard. Moreover, it saves power by going to deep sleep mode. In this mode, LoPy only consumes about 25 μA current. Table. 1 shows specifications for both hardware and wireless standards available in LoPy.

TABLE 1. LoPy v1.0 hardware specifications.

Hardware	**Peripherals**	UART, I2C, SPI, CAN, JTAG, PWM, ADC, DAC, SD
	Source Input Voltage	3.5 V∼5.5 V
	Source Output Current	1.2 A
	Operation Temperature	40∼80
	Moisture Sensitivity Level (MSL)	1
Wi-Fi	**Tx Power**	+14 dBm
	Protocol	802.11 b/g/n/e/i
	Frequency	2.4 GHz ∼2.5 GHz
Bluetooth	**Tx Power**	+12 dBm
	Modes	Class-1, Class-2, Class-3 with Adaptive Frequency Hopping and NZIF with -97 dBm sensitivity
LoRa	**Frequency**	860∼1020 MHz
	Spreading Factor	6∼12
	Bandwidth	125∼500 KHz
	Bit Rate	0.24∼37.5 Kbps
	Sensitivity	-117∼-137 dBm

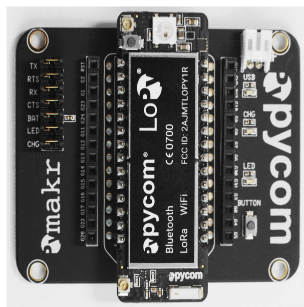

FIGURE 3. LoPy v1.0 on expansion board.

B. SOFTWARE

From the software end, Micropython was used as a programming language for the LoPy written on the ATOM IDE. Micropython is an extension of the python 3 language [35] to be able to run on microcontrollers. Micropython's interpreter called Repeat Evaluate Print Loop (REPL) resides directly on the microcontroller which subtracts excessive compilation steps to be performed when coding the hardware. Micropython contains almost all the core features that are available in the traditional Python 3 programming language. Micropython has built-in libraries that allow the user to directly control the hardware.

VII. PROCEDURE

A. ESTIMATION OF PATHLOSS EXPONENT

The first step in the experiment was to estimate the path loss exponent η used in (1) for each of the environments. To carry out this task one LoPy device was configured to transmit RSSI values and one was configured to receive the RSSI values for each of the three wireless standards at a distance

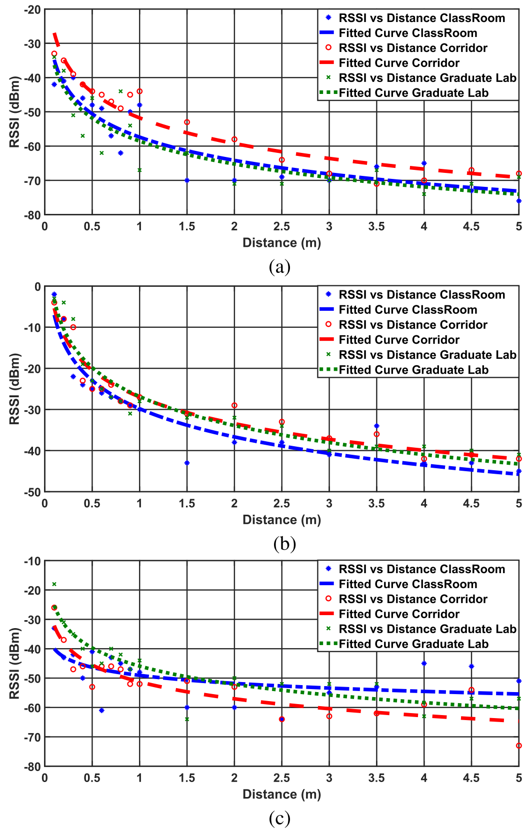

FIGURE 4. Fitted Curves for (a) BLE, (b) LoRa and (c) Wi-Fi in different locations.

ranging from 1 m to 3 m. In between 0 and 1 m, 9 points were taken and at each point, the RSSI value was recorded, and thereafter a difference of 0.5 m was taken between 1 and 3 m and after each 0.5 m distance, the RSSI values were recorded. The idea of recording RSSI values at fixed distances was to estimate η which reflects the rate at which the path loss changes with varying distances. These recorded RSSI values were provided to the MATLAB's *cftool* which estimated the value of the path loss exponent. Fig. 4 shows the fit curves for BLE, LoRa, Wi-Fi for all three locations. The path loss exponent values along with the system Loss constant for the three environments are shown in Table. 2

B. PERFORMING TRILATERATION

The second step in the experiment was to carry out trilateration. When using Wi-Fi, the device's internal 802.11n 2.4 GHz Wi-Fi chip was used. Also, two U.F.L connectors were available to connect external Wi-Fi antennae. To perform trilateration 3 LoPy devices were programmed to act as access points while one node was programmed to act as a station. The access points continuously relayed their SSID in addition to their RSSI values. The sensor node stored the received RSSI values in the internal memory for further calculations.

Similarly to perform trilateration using BLE the device's Bluetooth v4.2 (BLE) was used. Three nodes were programmed to act as advertisers and to continuously advertise the name and the manufacturer data. On the other hand, one device was programmed to keep scanning for available advertisements and if it receives one then it should extract the RSSI values from those advertisements and store them in the device's storage.

To perform trilateration using LoRa the device's LoRaMAC (also called Raw-LoRa) [36]functionality was used. Three LoPy devices were programmed as transmitting devices while one LoPy device was used as a sensor node. The transmitters continuously transmitted their unique node names that could be used by the sensor node to differentiate between different transmitting devices. The RSSI values were recorded by the sensor node and stored on the device's storage.

In the setup, three transmitters were placed according to the architecture shown in Fig. 2. The known distances selected were 1 m and 3 m respectively. The sensor node's location was varied in between nodes A and B, Nodes A and C, and then in the centroid of the triangle. The aim was to gather the RSSI values at each of the sensor node's locations and then take the average of those RSSI values. These averaged RSSI values are then used in (1) to estimate the actual coordinates of the sensor node. The estimated coordinates were compared with the actual coordinates using

$$er = \sqrt{(a_c - a_r)^2 + (b_c - b_r)^2} \tag{2}$$

where a_c, b_c are the calculated coordinates while a_r, b_r are the real coordinates. After determining the error between different wireless standards an average can be computed which will decide the most accurate wireless standard for all three environments. These results are shown in Figure. 5 respectively. An average of the error values was then taken to estimate the accuracy for each of the wireless technologies used.

TABLE 2. Pathloss exponent for class room, Corridor and graduate lab.

Location	Parameter	Wi-Fi	BLE	LoRa
Class Room	Path Loss Exponent (η)	0.907	2.256	2.280
	System Loss (γ)	-49.071	-57.375	-29.814
Corridor	Path Loss Exponent (η)	1.916	2.481	2.158
	System Loss (γ)	-51.286	-51.768	-26.953
Graduate Lab	Path Loss Exponent(η)	2.062	2.221	2.347
	System Loss (γ)	-45.919	-58.549	-26.850

VIII. RESULTS AND ANALYSES

This section gives an overview of the results presented as well as an appropriate analyses.

A. RESULTS

Experimental results are provided in Figure. 5. These show that of all three environments, BLE was the least accurate of all with an overall average error of 0.884 m. This is also shown in the classroom where BLE was most accurate with an average localization error of 0.679 m while in the corridor BLE's average error was found to be 1.2725 m which makes

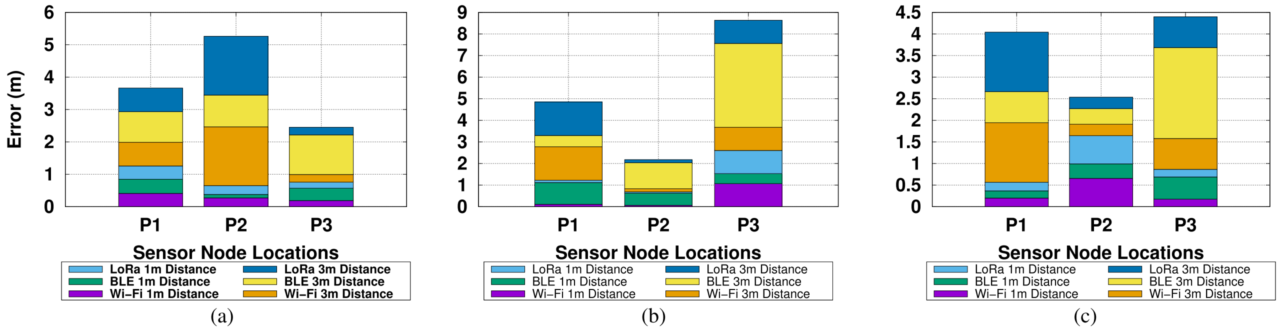

FIGURE 5. Error between real and estimated coordinates of sensor node in (a) Class Room (b) Corridor and (c) Graduate Lab.

it the least accurate in this environment. Similarly, in the graduate lab, its average error was 0.701 m. The second least accurate wireless technology was LoRa with an overall average error of 0.614 m. In the classroom, the average error was found to be 0.608 m which makes it most accurate in the classroom. Whereas, in the corridor, it was less accurate with an average error of 0.669 m. Moreover, in the graduate lab, LoRa's average error was 0.565 m. Of all the wireless standards used in the experiment, Wi-Fi was the most accurate with an overall average error of 0.555 m. Of all the environments, Wi-Fi was more accurate in the classroom with an average error of 0.507 m. Whereas, it was least accurate in the corridor with an average error of 0.652 m. It performed substantially better in the graduate lab with an average error of 0.507 m. By closely visualizing Figure. 5, the behavior of wireless standards with respect to distance can also be seen. In the classroom, when anchor nodes are placed at 1 m distance, the localization error of Wi-Fi, BLE, and LoRa was 0.160 m, 0.309 m, and 0.290 m respectively. When anchor nodes are placed at a distance of 3 m with each other, the error was 0.853 m, 1.049 m, and 0.927 m respectively for Wi-Fi, BLE, and LoRa. Similarly, in the corridor at 1 m distance between anchor nodes, the error was 0.291 m for Wi-Fi, 0.676 m for BLE, and 0.414 m for LoRa. When anchor nodes are placed at a 3 m distance, the error was 1.012 m, 1.869 m, and 0.924 m for the three standards respectively. Lastly, in the graduate lab, localization error was 0.145 m for Wi-Fi, 0.339 m for BLE, and 0.343 m for LoRa when anchor nodes are placed at 1 m distance. When placed at a 3 m distance, localization error for Wi-Fi, BLE, and LoRa was 0.869 m, 1.062 m, and 0.786 m respectively. From these values, it can be seen that localization error increases as distance among anchor nodes increase.

B. ANALYSES

Figure.5 and 6 provide useful insights. Localization accuracy is a function of several factors which include the power consumption of wireless standards, type of environment, other wireless interfering sources, etc. From the above figures, it can be seen that Wi-Fi performs better in all environments. This is because localization accuracy is dependent on RSSI variation [37]. This means more variation captures the effect

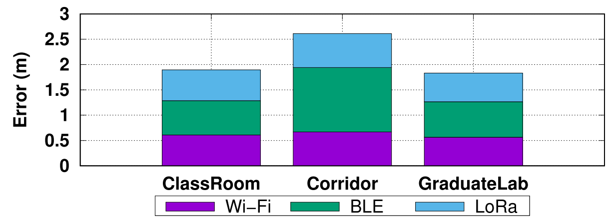

FIGURE 6. Location wise localization error.

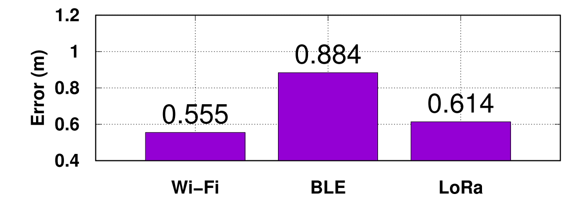

FIGURE 7. Average accuracy of wireless standards at different locations.

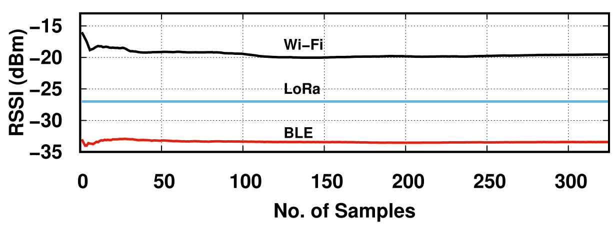

FIGURE 8. RSSI variation of wireless standards.

of its surrounding more effectively as compared to less variation. This is also seen in Figure. 8, where BLE and Wi-Fi show more RSSI variation than LoRa in our experiment. Wi-Fi operates in the 2.4 GHz band and its transmission radius are much greater than BLE. Moreover, Wi-Fi has greater penetration power which allows signals to penetrate objects much easier. Due to these properties, Wi-Fi has better localization accuracy. BLE on the other hand also operates in the 2.4 GHz band. It consumes less power than Wi-Fi. It's transmission/reception radius is much less than that of Wi-Fi which may require more devices to communicate with each other. Due to this increase in number, a high level of co-channel interference may exist as both Wi-Fi and other BLE devices operate in this band. At the time of the experiment, several Wi-Fi devices were operating which could be the cause of high-level interference. Due to these factors, BLE has shown to be least accurate in all environments. LoRa is designed to operate in the sub-GHz band which means that its transmission radius is much more than that of Wi-Fi and BLE. The only drawback of this standard is that it can only transmit a small amount of data in Kilobytes. Due to its large transmission/reception range, a fewer number of devices may be required for communication. This causes less interference with LoRa devices being used in localization.

Environment plays an important role in localization accuracy because of its surroundings which may include types of objects, walls, obstacles, etc. By looking at Figure. 6, one can see that all wireless standards show less localization error in the classroom. This may be because the room only contained wooden furniture with fewer wireless interfering sources such as Wi-Fi routers. Moreover, localization accuracy also depends on room area. Larger rooms tend to have fewer obstructions [38], which also increases localization accuracy. The area of the classroom was much larger than that of the remaining two environments which may have increased localization accuracy. The Graduate lab contained several computer systems as well as a considerable number of students using Wi-Fi/Bluetooth devices. This affects localization accuracy as is also seen in our findings. Lastly, while performing localization in the corridor, the error was much greater for all wireless standards. As can be seen from Figure. 2, narrow hallways were present which contribute towards multipath. Moreover, the presence of students within the corridor was considerably greater than in the other two environments. Usage of Wi-Fi-based mobile/laptop devices was also considerably greater. All these contribute to degradation localization accuracy. This can also be seen in the results.

Based on the above findings, we deduce that Wi-Fi is the best candidate for indoor localization. But if the localization system was powered with batteries then a Wi-Fi-based system would require charging the batteries more frequently. In this case, another alternative i.e. LoRa could be used. It has considerable accuracy and it also consumes less power. The only drawback of this standard is that the cost of LoRa based devices is comparatively higher than that of Wi-Fi and BLE. Therefore, if cost is not an issue, this standard should have opted. If the requirement of a localization system demands less power consumption and low cost then BLE-based devices can be used. The only drawback would be its less accuracy as well as more devices may be needed if a localization system is to be developed for larger distances.

IX. CONCLUSION

In this paper, a comparative study of different wireless technologies for indoor localization systems for the estimation of the sensor node's location is discussed. Path loss model is used which relates signal strength to distance. By using trilateration along with the path loss model an error between the actual and the calculated position is estimated and the results show that Wi-Fi is the most accurate for indoor localization followed by LoRa which is less accurate than Wi-Fi in the given environments but its long range makes it a perfect candidate without exposing extra hardware. The worst of all was BLE with the least accuracy than Wi-Fi and LoRa but due to its less power consumption, it can be the best solution in those environments localization systems need to operate on batteries.

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