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Indoor Location Sensing Using Multiple Wireless Standards

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Abstract

Indoor location sensing systems are crucial for Internet of Things advancements, providing essential location-based information for large-scale applications and systems. The existing literature usually involves designing and testing systems using a single wireless standard. Therefore, it is still uncertain what is the best wireless standard for indoor location sensing and whether there are any benefits to implementing cooperative location sensing. Therefore, an indoor location sensing system was developed, utilizing the RSSI fingerprinting method with K-Nearest Neighbours algorithm. The system was used to evaluate the individual performance of Wi-Fi, Bluetooth and ZigBee for indoor location sensing as well as validate if cooperative location sensing is feasible. For testing purposes, the test sites were split into grids of 1.5m by 1.5m size and the system made predictions on the correct grid position of the user device. The indoor location sensing system developed has an accuracy of 1.5m for a detection range of 10m. In terms of prediction accuracy, the system managed to achieve a maximum accuracy of 80.56% in non-Line of Sight scenario and a maximum accuracy of 100.00% in Line of Sight scenario. The prediction accuracy performance of the system in predicting the correct grid position varies depending on the combination of wireless standards used, with the best accuracy result being 100.00% when using a combination of Wi-Fi, Bluetooth and ZigBee in a Line of Sight scenario.

1. Introduction

Location sensing plays an important role in our daily lives in order to bridge the gap between the physical and digital world. The advancement of Internet of Things (IoT) requires one key feature which is the ability to provide location-based information for large-scale IoT applications and systems [1]. In this modern era, IoT has started to gain attention from many countries worldwide and Malaysia is no exception [2]. Examples of IoT in Malaysia include the UsherBots serving as guides at Sunway Carnival Mall [3] and waiter robots in several restaurants nationwide [4].

An indoor positioning system (IPS) refers to a system of network connected devices which can be used to wirelessly locate objects inside buildings or partially covered areas where GPS and other satellites lack precision [5]. An IPS is typically composed of three major stages [6]. In the first stage, location sensing devices are used to measure the important characteristics of a signal. Then in the second stage, range estimation devices make use of the measurement data to estimate the distance to/from the object that needs to be located. Finally, in the third stage, a combination of range estimates is used in order to predict and approximate the position of the object.

Currently, IPS widely makes use of radio frequency technology based on signal strength technologies and it uses narrow-band with spread-spectrum signals which are able to produce reliable and accurate results inside buildings [7]. There is growing demand in the area of location awareness, especially in the indoor space. The selection of a suitable wireless standard is crucial to design an accurate localization system. Examples of radiofrequency technology used in IPS include Wi-Fi, Bluetooth and ZigBee. There are several technologies developed only for indoor location sensing purposes, but they are not commonly used due to high-cost and sub-par performance [8].

In the existing related works, researchers have developed location sensing systems such as a Wi-Fi based indoor Location Based Service utilizing fingerprinting method [9], a mobile indoor positioning system application featuring Bluetooth beacons with trilateration method [10] and a convenient location positioning system using Wi-Fi with triangulation method [11]. However, the trend of the existing research is that researchers tend to test and design systems using only one type of wireless standard. Therefore, the major gap in existing works show that most researchers have not considered or tested the feasibility of using multiple wireless standards instead of just a single wireless standard. Another gap is that in order to create an accurate system which has less error in location sensing, more hardware needs to be implemented such as increasing the number of nodes in the system, but this increases the cost and complexity of the system.

The first technical objective of this project is to develop a system to evaluate the performance of Wi-Fi, Bluetooth and ZigBee for indoor location sensing. The second technical objective is to validate if cooperative location sensing is feasible for different wireless standards in indoor environments. The third technical objective is to develop an indoor location sensing system with an accuracy of 1.5m for a detection range of 10m. To summarize, this project focuses on indoor location sensing by comparing the different wireless standards and techniques used as well as exploring the possibility of using multiple wireless standards in the implementation of indoor location sensing. By doing so, this project can help to cover the gaps in existing research as well as optimize and facilitate the implementation and development of indoor location sensing in IoT systems.

2. Related Works

2.1 Comparison between Wi-Fi, Bluetooth and ZigBee Wireless Standards

The differences between Wi-Fi, Bluetooth and ZigBee are summarized in Table 1.

Table 1 *Comparison between Wi-Fi, Bluetooth and ZigBee*

	Wi-Fi [12] [13] [14]	Bluetooth [8] [15]	ZigBee [16] [17] [18]
Frequency Band	2.4 GHz and 5.0 GHz	2.4 GHz	2.4 GHz
Data Rate	1.0 Mbps	0.250 Mbps	54.0 Mbps
Coverage Range	100 m	10 m	10 m
Power Consumption	High	Low	Very Low
Cost	High	Low	Low
Complexity	High	Low	Low
Advantages	Easy to deploy and can cover large regions	Fast transmission speed and more secure	Can support thousands of nodes under a single network
Disadvantages	Accuracy depends on the amount of access points	Only allows short-range communication between devices	Prone to network interferences

Based on Table 1, it can be seen that all three wireless standards operate on the 2.4 GHz frequency band but Wi-Fi is also capable of operating on the 5.0 GHz frequency band. Making use of the 5.0 GHz frequency band allows Wi-Fi to operate with less interference from other devices compared to Bluetooth and ZigBee which need to share the same 2.4 GHz frequency band.

Wi-Fi has an advantage over Bluetooth and ZigBee in terms of coverage range as it can cover 10x the distance compared to Bluetooth and ZigBee. This makes Wi-Fi more suitable for long-distance transmissions.

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As for the power consumption, the difference between Bluetooth and ZigBee are minimal but both wireless standards have relatively better performance compared to Wi-Fi which consumes a lot of power because it involves high-bandwidth networks. Meanwhile, both Bluetooth and ZigBee are power-efficient because they are able to enter sleep mode when the device is not in use, reducing data and power usage.

For Wi-Fi, it can cover a large region compared to Bluetooth and ZigBee. However, its accuracy depends on the number of access points which can lead to higher cost if more access points are needed to achieve the desired accuracy.

For Bluetooth, it has fast transmission speed and is secure because it usually involves direct pairing between two devices for communication instead of using a lot of devices. However, the drawback is that it only allows short-range communication between devices.

For ZigBee, it can support thousands of nodes under a single network by making use of the "Mesh" topology but it is prone to network interferences from signals sharing the 2.4 GHz frequency band.

To summarize, each wireless standard has its merits and can be used for different scenarios. For instance, Wi-Fi is suitable when long-range transmissions with high accuracy is required while Bluetooth and ZigBee can be considered for short-range transmissions which require low power consumption to save cost. It is important to know how each wireless standard performs in different situations so that the most suitable wireless standard can be selected to develop an indoor location sensing system. The next sub-chapter discusses the fingerprinting, trilateration and triangulation methods because these three methods have previously been used by researchers and are also compatible with the Wi-Fi, Bluetooth and ZigBee wireless standards for the development of an indoor location sensing system.

2.2 Comparison between Fingerprinting, Trilateration and Triangulation Methods

The fingerprinting positioning method is a technique that relies on making use of the signal strength data measured between receiver antennas and the object. This signal strength data is also known as the Received Signal Strength Indicator (RSSI). The RSSI can be used to calculate the propagation loss for distance estimation purposes. Trilateration is a method that involves determining the object's position by using three transmitters at specific set locations and their simultaneous range measurements. Triangulation method is about calculating the position of the object by making use of the distance between three transmitters and the object as well as the measured angle from the three transmitters to the object. Researchers make use of these three methods to develop indoor positioning systems depending on the indoor environment and design specifications because each method has its own advantages and disadvantages in different scenarios.

A group of researchers from Universiti Teknologi Malaysia have used the fingerprinting method with KNN algorithm to develop a Wi-Fi based indoor Location Based Service [9]. The authors have carried out extensive tests on various sets of values of K and APs to obtain the accurate results instead of just using a single set of K and AP values. The fingerprinting method is used because it is able to provide accurate and consistent results in indoor multipath environments.

In a research by Noertjahyana et al., the feasibility of using Bluetooth beacons in the trilateration technique was explored [10]. The authors have also explored the various factors that can affect the accuracy such as thickness and density of the object as well as the external environmental changes. The trilateration method is used because it is simple to use and can provide accurate prediction results as long as there are no significant changes in the indoor environment.

Researchers from the Moscow Power Engineering Institute have made use of the triangulation method to design a convenient location positioning system using Wi-Fi [11]. The authors have tested the triangulation method in several scenarios such as outdoor and indoor locations and then compared them to find out the strengths and weaknesses of the triangulation method in those scenarios. The triangulation method is used because it is low-cost and can provide high prediction accuracy, especially in Line of Sight scenarios.

The related works of fingerprinting, trilateration and triangulation are summarized in Table 2. In triangulation, the parameter Angle of Arrival (AoA) represents the direction that the signal is received from. Based on the comparison between the three methods in Table 2, triangulation is not very suitable for indoor location sensing as this method involves measuring the AoA which tends to have error in the angle measurements. Even a small error in the AoA measurement eventually leads to a large error in the accuracy of the location sensing, especially in large indoor multipath environments.

On the other hand, fingerprinting can provide accurate results, even in indoor multipath environments. It also has an advantage of being easy to use after the initial set-up. However, it is also the most complex method out of the three methods listed as it involves offline phase for data collection and online phase for data matching. Another disadvantage is that fingerprinting is time-consuming because a lot of RSSI data needs to be collected, especially in large indoor environments.

As for trilateration, it can be a simple and low-cost alternative for indoor location sensing provided that the average of multiple measurements of the RSSI data is taken to minimize the measurement error and obtain more accurate results. However, it should be noted that the accuracy of trilateration is significantly affected by changes in indoor environments, so it is not as robust as the fingerprinting method.

In terms of accuracy, the fingerprinting method is accurate up to 1.51m while trilateration and triangulation both have better accuracies of 1.00m. However, it should be taken into consideration that the set-up in all three cases is different which results in the different accuracy values. For the trilateration and triangulation methods, more nodes were utilized in the system design compared to the fingerprinting method which is a simpler system using less nodes.

Table 2 *Comparison between fingerprinting, trilateration and triangulation*

	Fingerprinting [9]	Trilateration [10]	Triangulation [11]
Summary	Divides the location into several areas and makes use of the signal strength data at each area.	Makes use of known distances to estimate and pinpoint the object's location.	Makes use of known angles to estimate and pinpoint the object's location.
Measurement Parameter Used	Received Signal Strength Indicator (RSSI)	Received Signal Strength Indicator (RSSI)	Angle of Arrival (AoA)
Accuracy	1.51m [19]	1.00m [20]	1.00m [11]
Advantages	- Provides accurate and consistent results. - Easy to deploy after initial system set-up.	- The average of multiple measurements can be taken to obtain more accurate results. - Simple and low-cost method.	- Easy to measure AoA for environments where there is Line of Sight (LoS) between the transmitters and object. - Low-cost method.
Disadvantages	- Complex because it involves offline and online phases. - Need a long time to collect RSSI data. - Requires a specific fingerprint map for different locations.	- Accuracy is significantly affected by the environmental changes in indoor environments. - Cannot be used in areas with irregular or complex topography.	- Not suitable for multipath indoor environments due to error in AoA measurement. - Need specific equipment for angle measurement (theodolite).

To summarize, each method has its advantages and disadvantages. Although all three methods are compatible with the Wi-Fi, Bluetooth and ZigBee wireless standards, the fingerprinting method is chosen to develop the indoor positioning system for this project as it is more robust and can provide accurate results in indoor multipath environments when compared to the trilateration and triangulation methods. Despite the fingerprinting method having a complex set-up and requiring a long time to collect the RSSI data, it is a good trade-off for its high accuracy and consistent performance.

3. Methodology and Implementation

3.1 Overall Block Diagram

The system consists of three main parts, which are the input, fingerprinting process and output. For Wi-Fi and BLE wireless standards, an ESP32 module was used as the user device. For ZigBee protocol, an XBee module was used as the user device. The user device transmits the Wi-Fi, Bluetooth or ZigBee signals which are then received by the access points which are also ESP32 or XBee modules, depending on the wireless standard being used. A coordinator was used to collect the RSSI data from each access point. In this system, the user device also acts as the coordinator so the access points return the transmitted signal to the coordinator which then measures the RSSI data for the signals returned by each access point and this data is inputted into the fingerprinting database. This process is repeated several times for every reference point until sufficient data is obtained for the fingerprinting algorithm training process. The user device/coordinator is connected to a laptop, so an external power supply is not required. However, a powerbank was used to act as an external power supply for the access points.

During the fingerprinting process, the RSSI data in the fingerprinting database was stored in a CSV file and read using a Python script in Visual Studio Code software. The role of the localization algorithm is to match each

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set of RSSI data to a specific reference point during the offline training process. The localization algorithm used in this system is the K-Nearest Neighbours (KNN) algorithm.

Finally, a fresh set of RSSI data was obtained by moving the user device around the reference points. This RSSI data was used in the online testing phase to test the accuracy of the fingerprinting algorithm using different wireless standards or combination of wireless standards. The fingerprinting algorithm compared the new RSSI data to the existing RSSI data in the fingerprinting algorithm so that the resulting output can be obtained which is the predicted live location of the user.

The overall block diagram of the system is shown in Fig. 1.

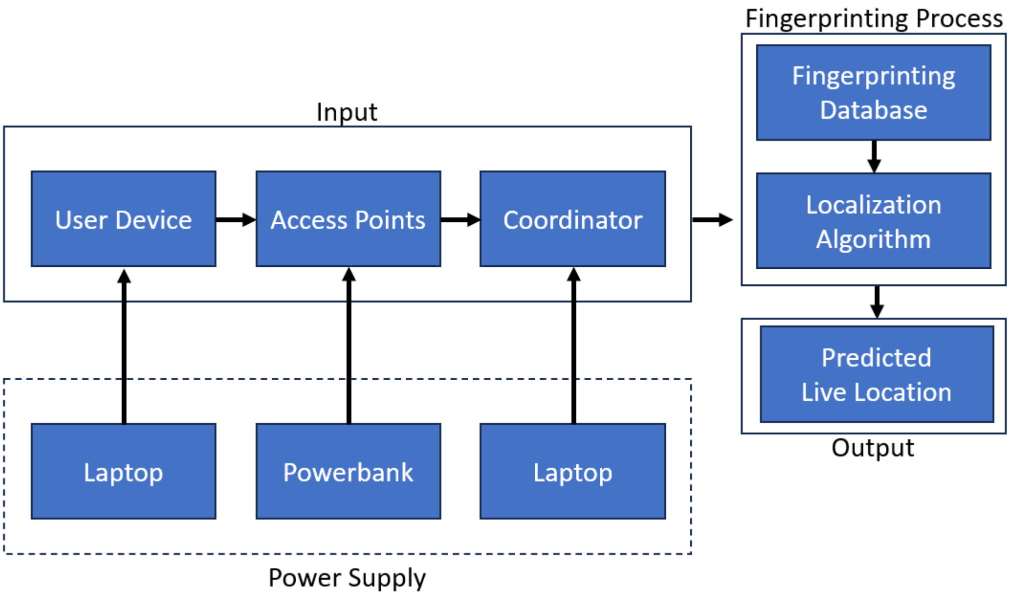

Fig. 1 *Overall block diagram*

3.2 Flowcharts for Fingerprinting Method

The Fingerprinting method can be divided into two phases which are the Offline Training Phase and Online Testing Phase. The flowcharts in Fig. 2 and Fig. 3 give an illustration of the Offline and Online phases, respectively.

3.2.1 Flowchart for Offline Training Phase

The Offline Training Phase of the Fingerprinting method focuses on data collection and training the fingerprinting algorithm. The first step is to divide the indoor location into several grid RPs. In this project, the user device and APs used were ESP32 microcontrollers for Wi-Fi and BLE wireless standards. XBee modules were used to act as the user device and APs for ZigBee protocol. The APs were placed at the corners of the indoor site while the user device was moved around each RP. The APs collect the RSSI data of the signal transmitted by the user device by using invasive detection and send the data to the coordinator to store the data in the fingerprinting database. The data collection process is repeated, and the average of the results is taken to obtain more accurate results. Then, the raw RSSI fingerprint data generated undergoes a position training algorithm which is the KNN algorithm. The end result is the generated fingerprint database which is used later on during the online phase to run matching algorithm and predict the live location of the user device.

The flowchart for the Offline Training Phase of the Fingerprinting method is shown in Fig. 2.

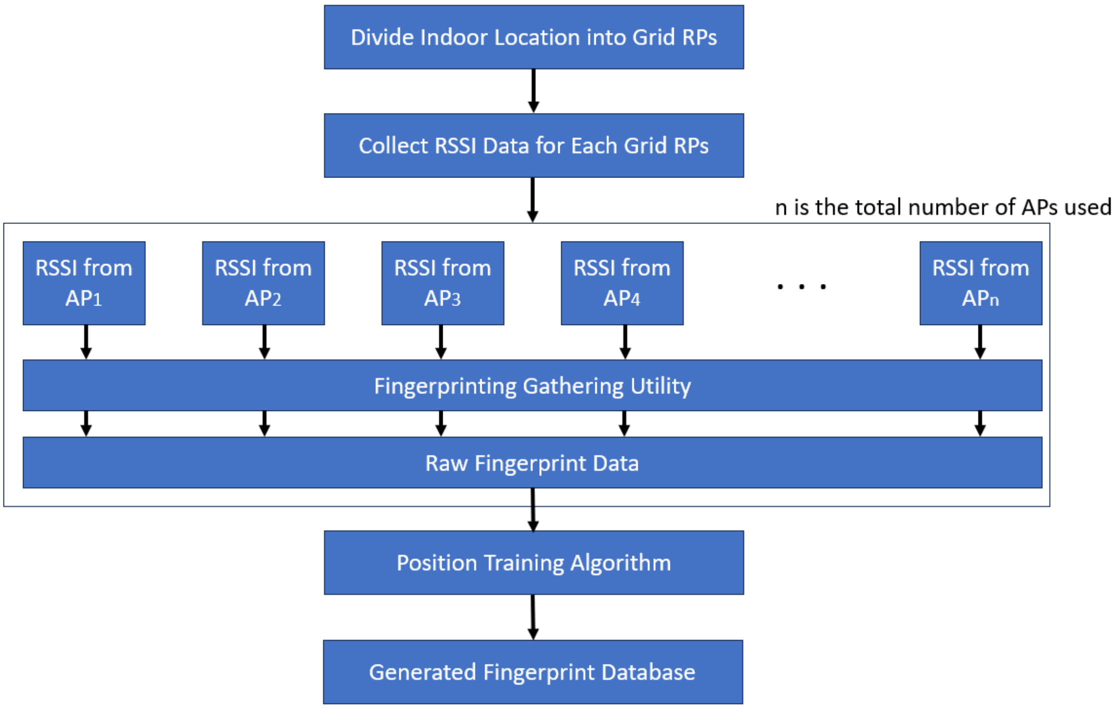

Fig. 2 *Flowchart for the offline training phase of the fingerprinting method*

3.2.2 Flowchart for Online Testing Phase

The Online Testing Phase of the Fingerprinting method focuses on predicting the live location of the user device. The process is quite similar to the data collection phase explained previously. The user device at any RP transmits a signal which is then received by the APs and sent to the coordinator. The new set of RSSI values obtained from each AP is then compared to the existing set of RSSI values in the fingerprinting database. The KNN algorithm then matches the user device's RSSI fingerprint to the closest RSSI fingerprint in the database to predict the live location of the user.

The flowchart for the Online Testing Phase of the fingerprinting method is shown in Fig. 3.

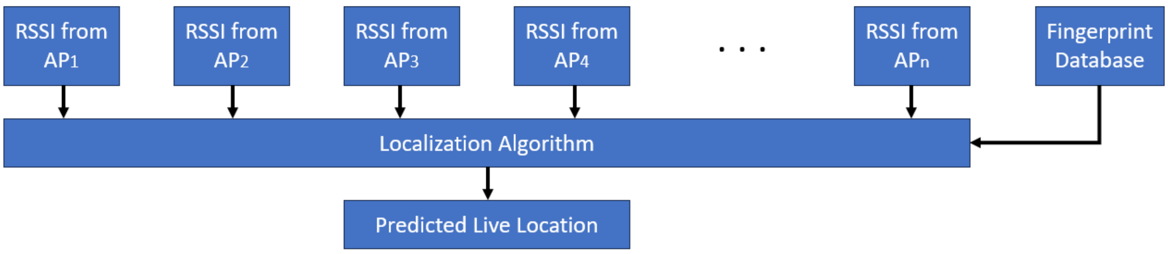

Fig. 3 *Flowchart for the online testing phase of the fingerprinting method*

It can be assumed that when the indoor location is divided into 1.5m x 1.5m grids and the user is predicted to be at the middle position of each grid, then the accuracy is 0.75m + 0.75m = 1.5m (1.5m is the total distance from the center of one grid to another adjacent grid) which means it is possible to achieve the technical objective of developing an indoor location sensing system with an accuracy of 1.5m for a detection range of 10m.

3.3 K-Nearest Neighbours (KNN) Algorithm

The fingerprinting method makes use of the K-Nearest Neighbours (KNN) algorithm for the position training algorithm. Selecting a proper K value is also important as the K value defines the number of neighbours in the algorithm. It is important to ensure that the K value is not too low or high because an extremely low K value leads to overfitting while an extremely high K value leads to underfitting, and both of these cases causes error during the prediction process. Generally, the value of K is taken as the square root of the number of data points used.

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It is expected that the training data consists of 10 data points for each reference point. Also, for classification cases, K is usually set as an odd value to avoid ties. Therefore, K = 3 would be a suitable value to use for the fingerprinting algorithm as it is an odd number to prevent ties and also fits the number of data points used for training. This helps to reduce the probability of overfitting or underfitting from occurring.

3.4 UML State Diagram for System Hardware

The system hardware setup consists of four main parts which are the user device/coordinator, access points, powerbank and laptop. The UML State Diagram for the system hardware is shown in Fig. 4.

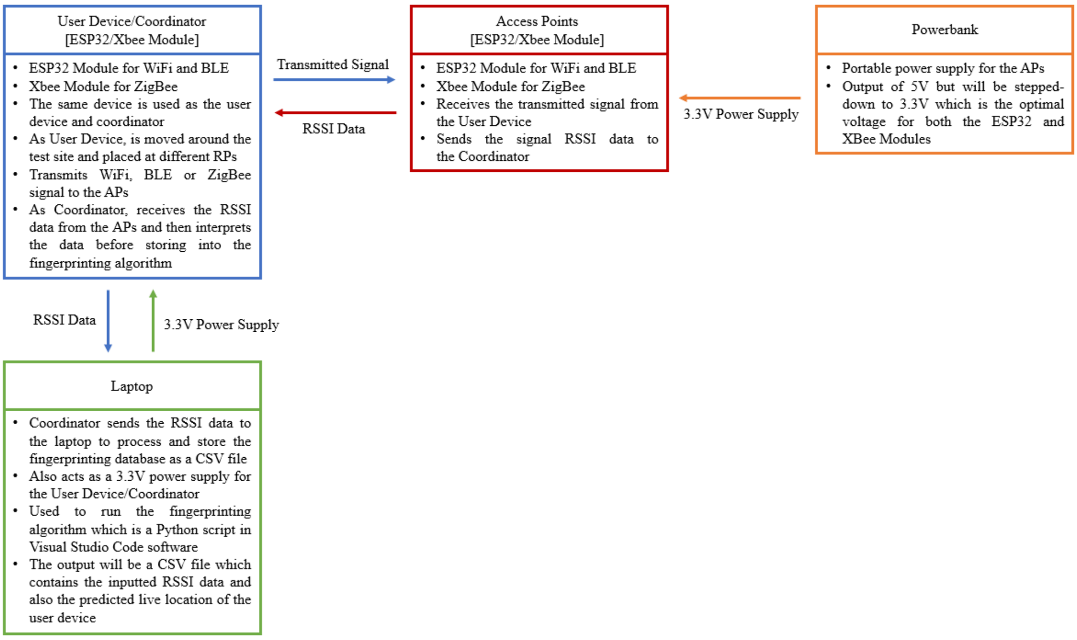

Fig. 4 *UML state diagram for system hardware*

3.5 UML State Diagram for Fingerprinting Algorithm

The fingerprinting algorithm was written as a Python script making use of data parsing and the KNN classifier. The UML State Diagram for the fingerprinting algorithm is shown in Fig. 5.

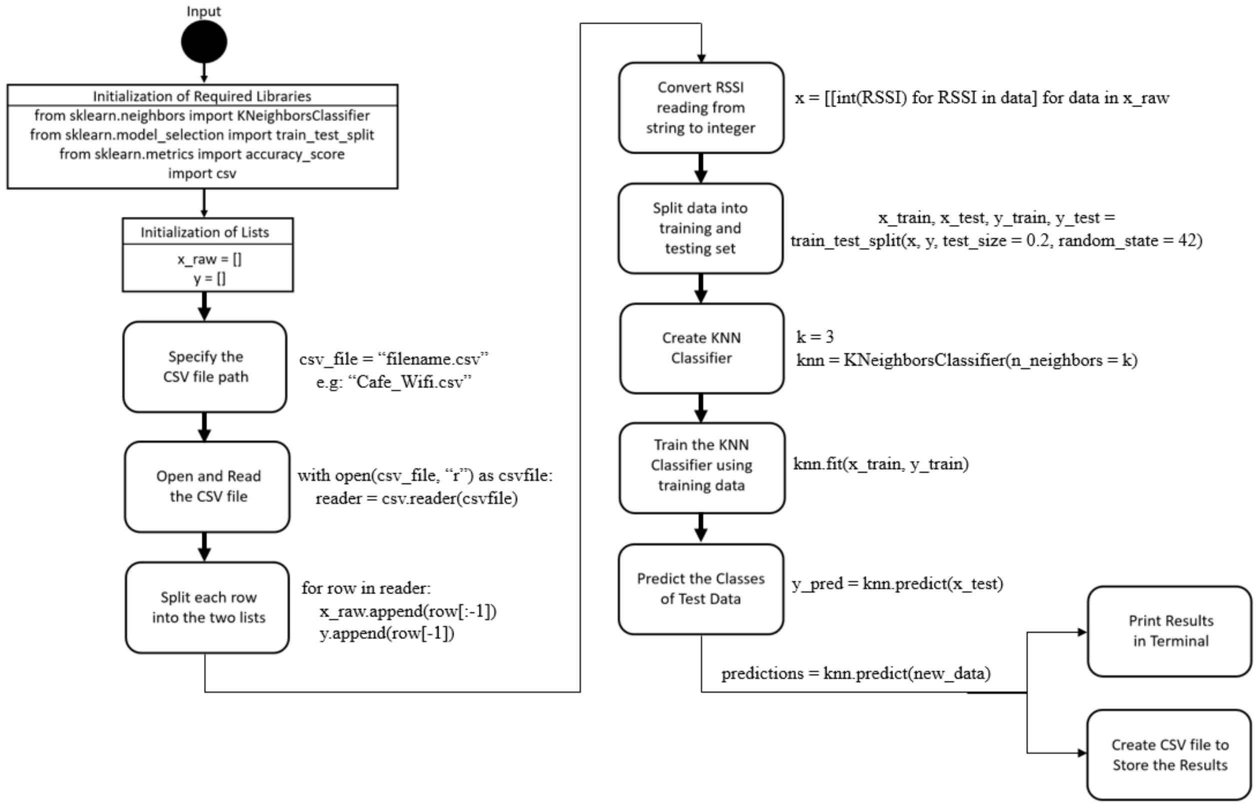

Fig. 5 *UML state diagram for fingerprinting algorithm*

3.6 Design of Experiment

Design of Experiment (DoE) makes use of controlled experiments to obtain data which can be analysed and interpreted to investigate the effects of the input factor(s) on the responding variable(s) [21]. In this DoE, the Full Factorial method is the most suitable as only two factors are being tested which are the "Distance" and "Wireless Standard". Furthermore, it is expected that these two factors have a strong and significant interaction which affects the RSSI reading of the signal.

The DoE involves two factors: Distance and Wireless Standard. Each factor has three levels which are 2m, 5m and 10m for Distance while the three levels are Wi-Fi, BLE and ZigBee for Wireless Standard. The list of factors and their respective levels for the DoE is shown in Table 3.

Table 3 *List of factors and their respective levels for DoE*

Factors	Level 1	Level 2	Level 3
Distance	2m	5m	10m
Wireless Standard	Wi-Fi	BLE	ZigBee

For the DoE, the following conditions were set:

- There is a clear Line of Sight between the transmitter and the receiver
- The transmitter and the receiver are both be placed at ground level for all experiments
- Only one wireless standard is active for each experiment
- The distance level covered is up to 10m in order to align with the third technical objective

For this project, the DoE full factorial template is generated using Minitab for the Distance and Wireless Standards factors with three levels each. The three levels for Distance are 2m, 5m and 10m while the three levels are Wi-Fi, BLE and ZigBee for Wireless Standard. For the DoE process, each experiment is conducted twice and the average of 10 data readings is taken as the result for each experiment to improve the reliability of the data. A total of 180 data readings are taken for the DoE process (3 Wireless Standards x 3 Distances x 2 Repetitions x 10 Data for each experiment = 180 Readings).

A unique aspect to the data collection is that Minitab allows users to have a randomized arrangement of experiments by assigning a seed to the built-in randomizer. Therefore, the randomized feature can help to reduce biasness during the data collection process. The set-up for the data collection process is shown in Fig. 6.

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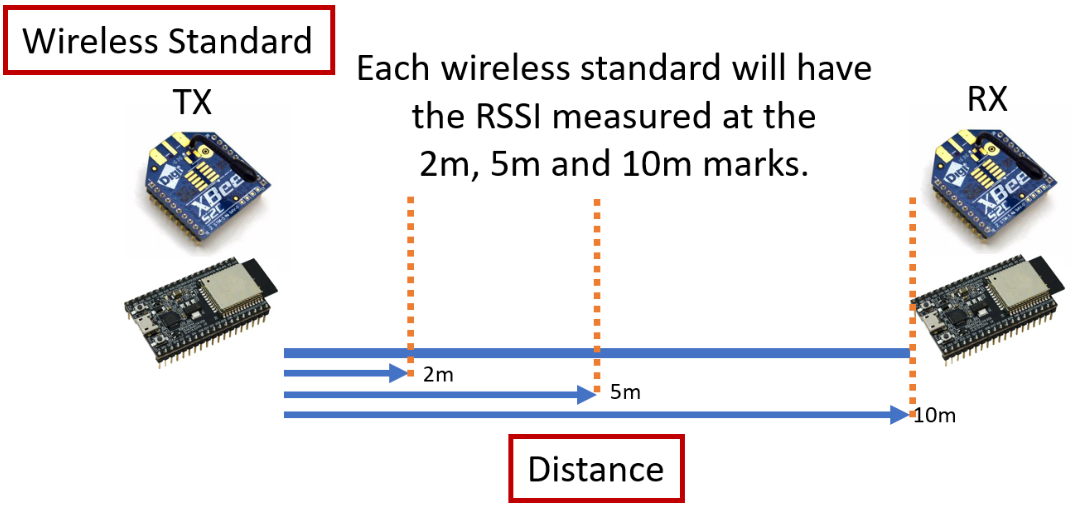

Fig. 6 *Set-up for full factorial DoE data collection*

The Analysis of Variance and Pareto Chart with the value of α = 0.05 to represent a confidence level of 95% can be used to validate that the two factors of Distance and Wireless Standard have a significant interaction with the RSSI reading. Meanwhile, the Interaction Plot for RSSI can be used to determine if there is any significant interaction between the wireless standards at different distances.

It should be noted that the data collection for the full factorial DoE was carried out along the indoor hallway of one of the test sites. Both the transmitter and receiver were placed at the same height which is ground level.

3.7 Site Layout and Set-up

The two test sites used for data collection are referred to as INTI and Cafe. For the INTI test site, it is a hallway covered by three walls and has one open wall. Meanwhile, the Cafe site is a partially-enclosed area. Both sites are covered with a roof.

The testing phase makes use of the RSSI readings as the user device passes through the RPs in three different scenarios which resemble how a human would walk in real-life:

- Walking in a straight line
- Walking in a zig-zag pattern
- Walking in a straight line then shift to another straight line at half-way point

Each scenario is carried out twice, using half of the RPs during the first run and the other half of RPs during the second run for a total of six paths.

The layout of both test sites is drawn and shown in Fig. 7. The green circles indicate the location of the APs while grids of 1.5m x 1.5m area are used for each RP. The six paths are also shown in Fig. 7. Each arrow resembles a path and for each RP in the path, two readings are taken to test the prediction accuracy of the fingerprinting algorithm using different wireless standards or combination of wireless standards.

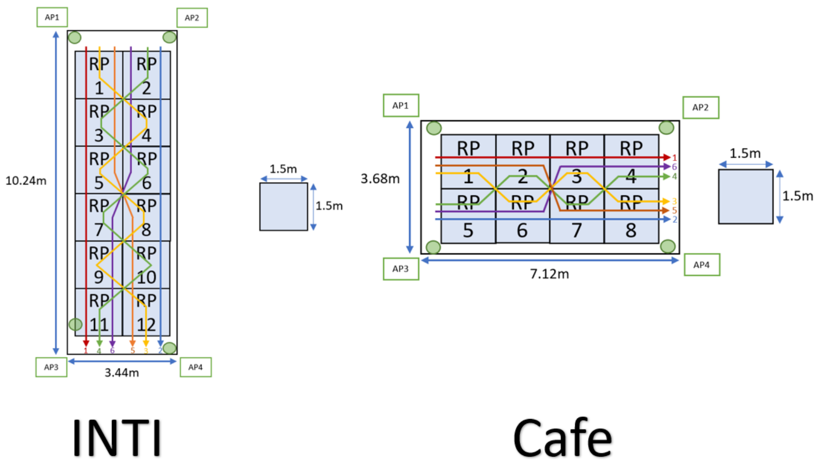

Fig. 7 *Site layouts and six paths for the online testing phase*

4. Results and Discussion

4.1 Design of Experiment

The Analysis of Variance, Pareto Chart and Interaction Plot for RSSI are plotted and the results are shown in Fig. 8 to Fig. 10.

With reference to Fig. 8 and Fig. 9, the value of α = 0.05 was used to represent a confidence level of 95% because that is the standard value typically used in statistics to represent the cutoff for significance [22].

The Analysis of Variance shows that the P-Value for both the Distance and Wireless Standard factors are 0.000 which is below the selected α-level of 0.05, indicating they have a significant interaction with RSSI readings. Meanwhile, the interaction between Distance and Wireless Standard is also significant at 0.004 but not as important as the individual factors. The Pareto Chart further supports this by showing that both factors are over the red line representing significance.

Factor Information

Factor	Levels	Values
Distance	3	2, 5, 10
Wireless Standard	3	WiFi, BLE, ZigBee

Analysis of Variance

Source	DF	Adj SS	Adj MS	F-Value	P-Value
Model	8	3672.71	459.09	277.02	0.000
Linear	4	3616.57	904.14	545.58	0.000
Distance	2	1055.28	527.64	318.39	0.000
Wireless Standard	2	2561.28	1280.64	772.76	0.000
2-Way Interactions	4	56.14	14.04	8.47	0.004
Distance*Wireless Standard	4	56.14	14.04	8.47	0.004
Error	9	14.91	1.66		
Total	17	3687.62			

Fig. 8 *Analysis of variance*

Meanwhile, the Interaction Plot for RSSI shows that each wireless standard has a different range of RSSI values at different distances. It is expected that ZigBee has the strongest RSSI values, followed by Wi-Fi and finally BLE. However, this does not guarantee that ZigBee has the best performance for indoor location sensing as other factors such as standard deviation and prediction accuracy still need to be evaluated. Nevertheless, the knowledge that each wireless standard has a different range of RSSI values that do not overlap with each other opens up the possibility of implementing cooperative location sensing.

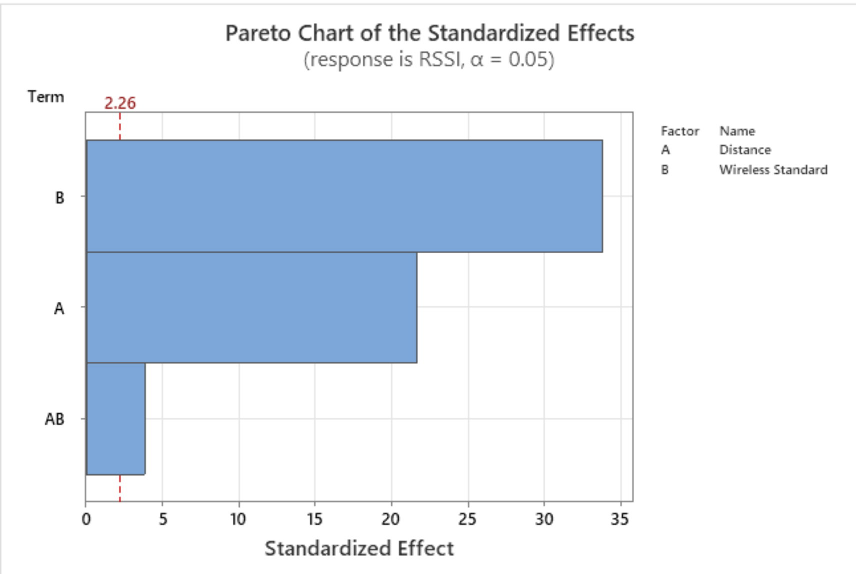

Fig. 9 *Pareto chart*

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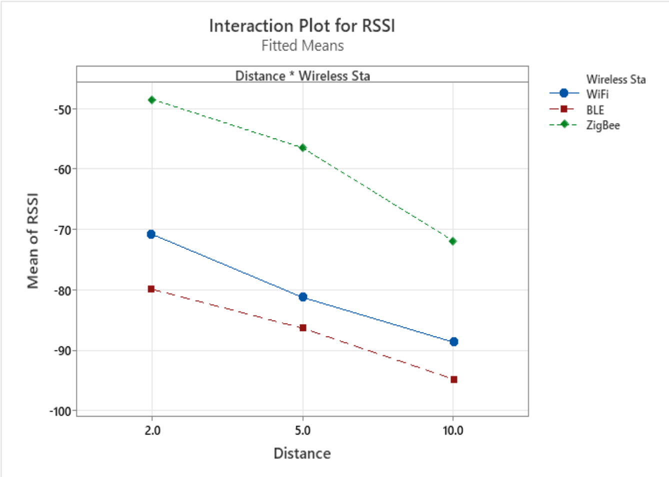

Fig. 10 *Interaction plot for RSSI*

Hence, the technical objective of determining the best-performing wireless standard for indoor location sensing can be achieved as it has been validated from the full factorial DoE that the Distance and Wireless Standard factors have a significant interaction with RSSI readings. Also, validating the feasibility of cooperative location sensing can be achieved by combining the RSSI readings of different wireless standards for the fingerprinting algorithm instead of just using a single wireless standard because each wireless standard has a different range of RSSI readings that do not overlap with each other.

4.2 Fingerprinting Algorithm

Previously during the DoE, only one wireless standard was active for each experiment. This means that only the interaction between an individual wireless standard and distance was explored. For example, the RSSI for Wi-Fi is measured at 2m, 5m and 10m distances then this process is repeated for the BLE and ZigBee wireless standards in separate experiments.

In order to explore the feasibility of combining multiple wireless standards in indoor positioning systems, the RSSI database of each wireless standard can be combined into a single CSV file containing the RSSI databases of Wi-Fi, BLE and ZigBee so that the Python script in Visual Studio Code software can read and make use of the RSSI data for all three wireless standards during the localization algorithm in the offline training process instead of just using the RSSI data for an individual wireless standard.

A total of 2400 RSSI readings were taken to train the fingerprinting algorithm according to the Site Layout and Set-up plan in the Methodology and Implementation chapter. (4 APs x 20 RPs x 3 Wireless Standards x 10 Repetitions = 2400 Readings). At each RP, 10 sets of RSSI readings were recorded for AP1, AP2, AP3 and AP4 for each wireless standard. The standard deviation of the RSSI readings were also calculated. Then, the RSSI training data is transferred to a CSV file that can be read by Visual Studio Code.

The next step is to record a new set of RSSI data following the plan previously mentioned in the Methodology and Implementation chapter. In the Python script, the CSV file path is specified so that it can be read by Visual Studio Code. The CSV can also be considered as the fingerprinting database as it contains all the necessary RSSI information as well as which AP it belongs to. Each wireless standard or combination of wireless standard has its own CSV file. The possible combinations are:

- Wi-Fi
- BLE
- ZigBee
- Wi-Fi + BLE
- Wi-Fi + ZigBee
- BLE + ZigBee
- Wi-Fi + BLE + ZigBee

Therefore, there are 14 CSV files in total (7 for each test site). Then, the new RSSI data is inputted for the Online Testing Phase. During the testing phase, the new RSSI data is matched to the existing data in the fingerprinting database. The KNN algorithm is used to predict the live location of the user device and the output is stored in a CSV file. Finally, by using the output CSV file, the predicted location is compared with the actual location to determine the prediction accuracy for each wireless standard or combination of wireless standards.

An example of how Visual Studio Code reads the CSV file then uses KNN for the fingerprinting algorithm to predict the live user location using the new set of RSSI data is shown in Fig. 11.

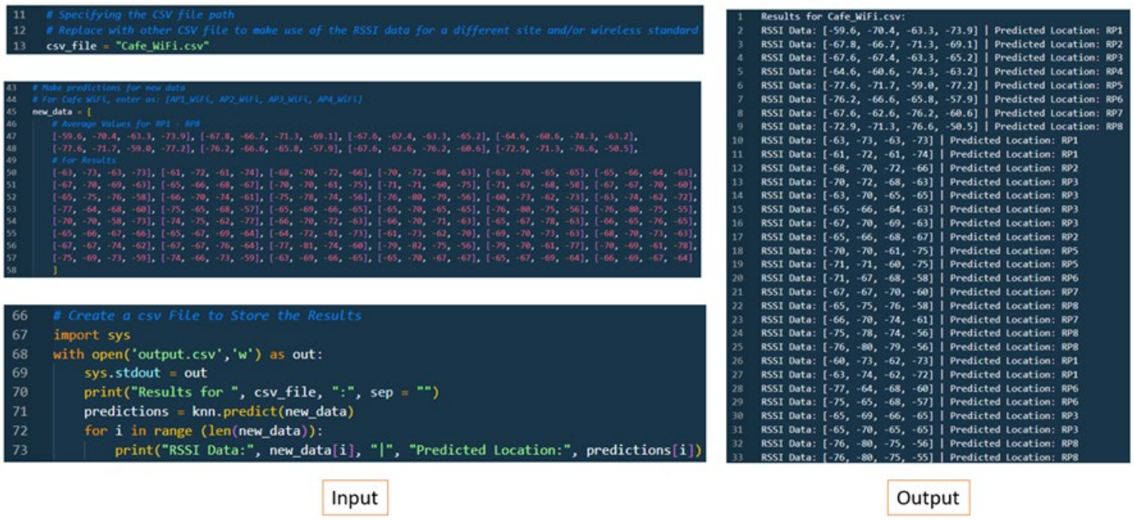

Fig. 11 *Example of the fingerprinting algorithm using visual studio code*

The overall performance results of the wireless standards are then evaluated using the average overall standard variation as well as the prediction accuracy results obtained after comparing the live location of the user to the predicted location using the fingerprinting database.

It is important to note that each wireless standard processes multipath differently and this can have an impact on wireless systems [23]. Therefore, the standard deviation for the RSSI values as well as the fingerprinting algorithm's prediction accuracy performance using each wireless standard must be taken into consideration. With reference to Table 4 and Table 5, Wi-Fi has a relatively low standard deviation in both test sites when compared to the other two wireless standards which have the lowest standard deviation in one site but a significantly higher standard deviation than Wi-Fi in the other test site. ZigBee which is using an external whip antenna on the XBee modules is more affected by obstructions in-between the transmitter and receiver devices which causes the RSSI readings to have a much higher standard deviation in the INTI area when compared to Wi-Fi and BLE which are both using an internal antenna in the ESP32 modules.

Table 4 *Standard deviation performance of each wireless standard individually for cafe site*

Wireless Standard	Overall Standard Deviation
Wi-Fi	1.4795
BLE	1.7043
ZigBee	1.2205

Table 5 *Standard deviation performance of each wireless standard individually for INTI site*

Wireless Standard	Overall Standard Deviation
Wi-Fi	1.3760
BLE	1.2972
ZigBee	2.3101

In terms of prediction accuracy, it can also be observed that Wi-Fi has more correct predictions and hence, a higher accuracy than BLE and ZigBee in both test sites. Therefore, the first technical objective has been achieved by identifying Wi-Fi as the best performing wireless standard for indoor location sensing as it has relatively low standard deviation and is the most consistent in producing accurate predictions individually when compared to BLE and ZigBee.

As for validating if cooperative location sensing is feasible using multiple wireless standards, the RSSI fingerprinting database for Wi-Fi, BLE and ZigBee were combined and then the prediction accuracy was calculated for each of the combinations to test if the prediction accuracy can be improved. Based on the results in Table 6 and Table 7, it can be observed that a combination of wireless standards can produce higher accuracy when compared to their individual counterparts. This is because a combination of wireless standards can help to identify and correct the prediction errors made by a single wireless standard.

However, it is important to note that sometimes even the combination of wireless standards is unable to predict the correct location if the prediction errors overlap and occur at the same test. For example, the Cafe area has prediction errors occurring at different tests for the individual wireless standards while the INTI area has prediction errors occurring at the same tests. Hence, the Cafe area was able to achieve a maximum prediction accuracy of 100.00% when using a combination of Wi-Fi + BLE + ZigBee while the INTI area was only able to achieve a maximum prediction accuracy of 80.56% because of the incorrect prediction for some tests.

Table 6 *Prediction accuracy results for cafe site*

Wireless Standard(s)	Correct Predictions	Result	Accuracy (%)
Wi-Fi	39/48	0.8125	81.25
BLE	31/48	0.6458	64.58
ZigBee	34/48	0.7083	70.83
Wi-Fi + BLE	45/48	0.9375	93.75
Wi-Fi + ZigBee	45/48	0.9375	93.75
BLE + ZigBee	45/48	0.9375	93.75
Wi-Fi + BLE + ZigBee	48/48	1.0000	100.00

Table 7 *Prediction accuracy results for INTI site*

Wireless Standard(s)	Correct Predictions	Result	Accuracy (%)
Wi-Fi	45/72	0.6250	62.50
BLE	43/72	0.5972	59.72
ZigBee	32/72	0.4444	44.44
Wi-Fi + BLE	52/72	0.7222	72.22
Wi-Fi + ZigBee	42/72	0.5833	58.33
BLE + ZigBee	49/72	0.6806	68.06
Wi-Fi + BLE + ZigBee	58/72	0.8056	80.56

Therefore, the second technical objective has been achieved by validating that cooperative indoor location sensing using multiple wireless standards is indeed feasible. Higher prediction accuracy can be achieved when using a combination of wireless standards compared to just using a single wireless standard.

Another observation from the data is that the overall accuracy is higher in the Cafe site compared to the INTI site. This is because there is Line of Sight (LoS) between the transmitter and receiver in the Cafe area while there are chairs which act as obstacles in-between the transmitter and receiver in the INTI site, creating a non-LoS scenario. These obstacles can cause phenomena such as reflection, diffraction and scattering when the transmitted signal comes into contact with the chair which affects the multipath of the signal. Hence, the overall accuracy is higher for LoS scenarios compared to non-LoS scenarios for indoor location sensing systems.

The system developed was able to produce an overall prediction accuracy in the range of 64.58% to 100.00% in the Cafe site and 44.44% to 80.56% in the INTI site depending on the type of wireless standard or combination of wireless standards used. Therefore, the third technical objective of developing an indoor location sensing system with 1.5m accuracy for a detection range of 10m has also been successfully achieved.

When comparing the developed system's results with existing related works, the system has a higher prediction accuracy of 81.25% in LoS scenarios for Wi-Fi compared to the 74% prediction accuracy of an existing system using fingerprinting method and 4 APs [9]. This shows that the performance of wireless standards such as Wi-Fi in indoor location sensing systems varies according to the layout of the test site.

Furthermore, the indoor location sensing system developed in this project using KNN algorithm has an accuracy of 1.5m which is 0.01m better than an existing indoor location sensing system using KNN algorithm with similar setup of 4 APs [19]. This shows that the developed system's performance is on-par with existing indoor location sensing systems.

Another comparison is that the aforementioned indoor location sensing system has also tried making use of the SVM algorithm but was only able to achieve an accuracy of 1.37m [19]. The system developed in this project using KNN algorithm has an accuracy of 1.5m which is 0.13m better than the SVM algorithm in related works. Therefore, the KNN algorithm is more reliable when compared to the SVM algorithm which is another commonly used algorithm for developing indoor location sensing systems, especially those using the fingerprinting method.

5. Conclusion

To summarize, an indoor location sensing system with an accuracy of 1.5m for a detection range of 10m was developed using the fingerprinting method and KNN algorithm. ESP32 and XBee modules were used to test Wi-

Fi, BLE and ZigBee to evaluate their overall performance in terms of standard deviation and prediction accuracy under both LoS and non-LoS scenarios.

The project can be considered a success as all three technical objectives were able to be achieved. Firstly, it has been successfully evaluated that Wi-Fi has the best individual performance for indoor location sensing in terms of 81.25% and 62.50% accuracy at the Cafe and INTI sites, respectively. Furthermore, Wi-Fi also has a lower overall standard deviation when comparing its RSSI values to BLE and ZigBee. However, cooperative location sensing using a combination of Wi-Fi, BLE and ZigBee produced the highest accuracy of 100.00% and 80.56% which are the best accuracies for the Cafe and INTI sites, respectively. Lastly, the indoor location sensing system developed was successful in obtaining results and is on-par with existing systems.

The project's contributions include identifying Wi-Fi as the best wireless standard for indoor location sensing and validating the feasibility of cooperative location sensing. These findings have paved the way for the development of better indoor location sensing systems as well as the exploration of using multiple wireless standards in indoor location sensing.

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Conflict of Interest

The authors declare that there is no conflict of interest regarding the publication of the paper.

Author Contribution

The authors confirm contribution to the paper as follows: ***study conception and design:*** *Shawn Tan Zhu Wen, Solahuddin Yusuf Fadhlullah;* ***data collection:*** *Shawn Tan Zhu Wen, Solahuddin Yusuf Fadhlullah;* ***analysis and interpretation of results:*** *Shawn Tan Zhu Wen, Solahuddin Yusuf Fadhlullah;* ***draft manuscript preparation:*** *Shawn Tan Zhu Wen, Solahuddin Yusuf Fadhlullah, Cheong Choon Min, Samihah Abdullah, Shabinar Abdul Hamid. All authors reviewed the results and approved the final version of the manuscript.*

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