Indoor Localization using Bluetooth (BLE) Beacons

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by

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BONA FIDE CERTIFICATE

This is to certify that the report titled **Indoor Localization using Bluetooth (BLE) Beacons**, submitted by **Abhishek Kaushik** and **Nilesh Tiwari**, to the Indian Institute of Technology, Tirupati, for the award of the degree of **Bachelor of Technology**, is a bona fide record of the project work done by them under my supervision. The contents of this report, in full or in parts, have not been submitted to any other Institute or University for the award of any degree or diploma.

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ABSTRACT

KEYWORDS: Indoor Localization; BLE Beacons; RSSI; Filtering; Kalman Filter; Moving Average Filter; RSSI Distance Model; Weighted k Nearest Neighbors; Nonlinear Least Squares.

GPS-based positioning technology enables to develop Location-based services (LBS) in outdoor environments such as outdoor navigation systems, which are used by many people in everyday life. The signal strength of GPS is very poor in indoor environments, so there is need of other technologies to provide similar applications and services indoors. Indoor navigation, marketing services, and emergency services are some important applications of indoor localisation systems. Hence, it becomes very important to have indoor localization models for different kinds of environments such as a big hall and a corridor. In this work, we present an indoor localization system built using BLE beacons for three different experimental environments and apply two fingerprint location algorithms namely Weighted k Nearest Neighbors (WKNN) and Nonlinear Least Squares (NLLS). We vary different parameters(filtering method, localization algorithm and fingerprint dimensionality) to achieve the best results and determine useful fingerprint dimensionality and get mean absolute error (MAE) of 1.11m for Hostel Block-C Corridor (36m x 1.8m), 1.59m for IITT Computer Centre (11.4m x 11.4m) and 1.16m for IITT Library (11.6m x 8.4m). We obtained best MAE of 1.11m for the corridor, and more than 65% of points under MAE of 1m for the library.

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ABBREVIATIONS

BLE	Bluetooth Low Energy
BPNN	Back Propagation Neural Network
GPS	Global Positioning System
IITT	Indian Institute of Technology Tirupati
KNN	K Nearest Neighbors
LBS	Location Based Services
LoRa	Long Range
LOS	Line of Sight
MAE	Mean Absolute Error
NLLS	Nonlinear Least Squares
PDR	Pedestrian Dead Reckoning
RFID	Radio Frequency Identification
RSSI	Received Signal Strength Indicator
RTT	Round Trip Time
UWB	Ultra Wideband
WKNN	Weighted k Nearest Neighbors

CHAPTER 1

INTRODUCTION

1.1 Indoor Localization

Indoor Localization is a technique used to locate any thing in indoor spaces. GPS provide accurate global position in outdoor environment but these signals are not suitable for indoor localisation as they can not penetrate buildings. GPS provides accuracy up to 5m in outdoors but in indoors, this amount of error is intolerable. Hence, there is need of other methods to provide more accurate indoor localisation systems. The most common technologies used for indoor spaces are WiFi and Bluetooth. Other technologies such as Radio Frequency Identification (RFID), Ultra-Wide Band (UWB), Long Range (LoRa), Zigbee, cellular signals and readings of embedded geomagnetic and light sensors are also commonly used. BLE approaches can be divided into 3 categories based on the technique used for localization; angle-based, range-based, and hybrid methods. Range-based approach is based on measurement of RSSI values. Range-based approach uses two methods: fingerprinting and trilateration (Subhan *et al.*, 2011). Fingerprinting is preferred over the trilateration method. The algorithms used for fingerprinting are KNN, WKNN, deep learning and neural network based (Zhang *et al.*, 2013).

In the fingerprinting method, the number of RSSI readings used for computing location of a point from a reference point is called fingerprint dimensionality. However, it is not necessary to use the RSSI readings from all the beacons (Faragher and Harle, 2015).

1.2 BLE Beacons

The most commonly used technology for indoor localization is WiFi but we have choosen BLE beacause of the advantages it has over WiFi.

- BLE beacons are portable, battery-powered and cheaper

- The BLE beacons report signal strength value in standard units of dBm. Whereas, WiFi access points are not bound to report signal strength value in any specific unit. (Faragher and Harle, 2015).
- BLE beacons can be easily deployed in any environment and they do not provide any communications coverage whereas in case of WiFi, access points are deployed basically for providing communications coverage.
- All recent smartphones support BLE, and beacons are less power hungry and smaller in size.

Beacons broadcast their identifier in form of advertisement signals to nearby receiver devices that support BLE signals, such as smartphones. Advertisement rate is the rate at which BLE signals are transmitted. The transmission range is directly affected by the transmit power. As the transmit power increases, the transmission range increases.

We used RadBeacon Dot as the transmitting device. The RadBeacon Dot proximity beacon is small in size, lightweight, and easy to deploy. RadBeacon Dot is shown in Fig.1.1 along with its specifications in Table.1.1.

Figure 1.1: RadBeacon Dot

Table 1.1: Beacon Specifications

Version	4.0 (Bluetooth Smart)
Frequency	2.402 GHz to 2480 GHz
Transmit Power	+4dBm to -20dBm
Transmission Range	50m
Advertisement Rate	1Hz - 10Hz
Size (L x W x H)	35 x 35 x 15mm

The beacons use the AltBeacon protocol. All of the beacons were configured at same advertisement rate of 1 Hz, and transmit power of 0 dBm.

1.3 Approach and Contributions

We evaluate a BLE-based fingerprinting system that assumes static BLE beacons deployed in the environment. We investigate two localization techniques; WKNN and NLLS. We further determine the fingerprint dimensionality needed for good localization for different environmental setups. The main contributions of this work are:

- a study into the key parameters of BLE localization for different environments for achieving good accuracy;
- impact of fingerprint dimensionality on error for mulitple localization algorithms.

CHAPTER 2

Literature Review

There has been an increasing attraction of researchers towards indoor localisation in recent years. This section puts knowledge and literature for different indoor localization technologies.

2.1 Existing work

A. Technologies used for indoor localisation

Many researchers have already done a comprehensive study on different localization techniques and these studies can be found in (Mainetti *et al.*, 2014), (Yassin *et al.*, 2016), and (Zafari *et al.*, 2019). Researchers in academia have used many technologies for indoor localization such as WiFi, Bluetooth, UWB, RFID, geomagnetic field, cellular signals, and PDR (Sakpere *et al.*, 2017).

The technologies like RF tags, and UWB can estimate the locations to cm level but they need specialised hardware and wide-ranging placement of infrastructure, which makes them costlier than other technologies and hence, are not commonly used (Ashraf *et al.*, 2020).

The cellular signals can be used for localization because all phones support cellullar technology. Localisation model based on cellular signal also does not use any extra power apart from normal phone operation. But the limitation of phones is that each cell phone can receive signals from at most seven cell towers (Rizk, 2019). Researchers use data augmentation techniques to increase the dataset when using cellular signals (Rizk *et al.*, 2019).

Geomagnetic field and visible light are omnipresent and can be exploited. However, the geomagnetic field intensity and visible light intensity are heavily infuenced by the environment. Hence, traditional methods can not be used to analyse the variation of geomagnetic field and visible light. So deep learning methods are required for localization (Wang *et al.*, 2019).

Indoor localization using WiFi is very popular beacause of the wide-spread coverage of WiFi, and no need of installing extra hardware as the existing infrastructure of WiFi access points can be used. The techniques based on WiFi include RSSI based (Abbas *et al.*, 2019), and RTT based (Hashem *et al.*, 2020).

Since the advent of BLE technology, WiFi and BLE are the two most popular technologies (Gang and Pyun, 2019). The BLE technology requires deployment of BLE beacons in the experimental environment. The BLE signals are affected by attenuation, multipath fading, and interference leading to fluctuations in indoor environment (Faragher and Harle, 2015).

Moreover, hybrid technologies that use a combination of other technologies prove more accurate. They are used to provide localization and positioning services for different environments like market places, and offices (Gang and Pyun, 2019).

B. BLE based Indoor localisation

Range-based approaches are used for BLE based indoor localisation which includes triangulation, trilateration, and fingerprinting. Fingerprinting is preferred over the other methods. The common methods used in fingerprinting are KNN, WKNN, NLLS, deep learning and neural network based.

Wang *et al.* (2013) came up with a Bluetooth-based trilateration method which included transmission from Bluetooth devices and positioning using trilateration, but it could only estimate approximate location of the user.

Many researchers have used the traditional logaritmic path-loss model to fit the RSSI distance model (Golestani *et al.*, 2014). Spachos and Plataniotis (2020) have investigated the localisation performance of the traditional logarithmic path-loss model for different types of testbeds like corridor and laboratory. But the logarithmic model can only be applied to accurately fit the curve if the signal is not too noisy. Shi and Zhang (2012) proposed a back propagation neural network (BPNN) based method for fitting the RSSI distance model, which improves the estimation accuracy but that too is not resistant to RSSI fluctuations. Li *et al.* (2018) proposed a RSSI Real-time correction algorithm where a bluetooth gateway receives the signals from other beacons in the environment and sends them to the server where the server estimates the fluctuation and corrects the RSSI before applying any filters to remove noise.

Determining optimal beacon density for an environment is an issue. Sadowski and Spachos (2019) have tried to come up with an optimal number of beacons that should be deployed in an environment for which the error is least. They have proposed that NLLS method with three reference points gives better accuracy than trilateration method. The beacon placement is another important issue as mentioned by Larsson (2015). People have used their own strategies in fixing the positions of the beacons that according to them suited their environments. Faragher and Harle (2015) contains a comprehensive study on the imapct of key parameters such as time window, advertisement rate, transmit power, and reducing beacon density. However, they didn't provide much insights on the effect of fingerprint dimensionality.

Ke *et al.* (2018) came up with a different application of BLE beacons. They proposed a system framework for a smart home power management system where BLE beacons are used for estimating the user's location and then performing power management in the home.

2.2 Variation in RSSI with time

Bluetooth devices don't transmit signals with fixed power. Hence, the RSSI values fluctuate with time (Li *et al.*, 2018). We tested the RSSI fluctuation of BLE beacons for a sampling period of 50 seconds as shown in Fig.2.1 and other for a longer period of 5 minutes as shown in Fig.2.2. Both of the RSSI values are fluctuating. Filtering is a method that is used for reducing errors that can occur due to RSSI fluctuations. Some of the most popular filters used are the moving average, and Kalman. We have applied both the filters on the RSSI values.

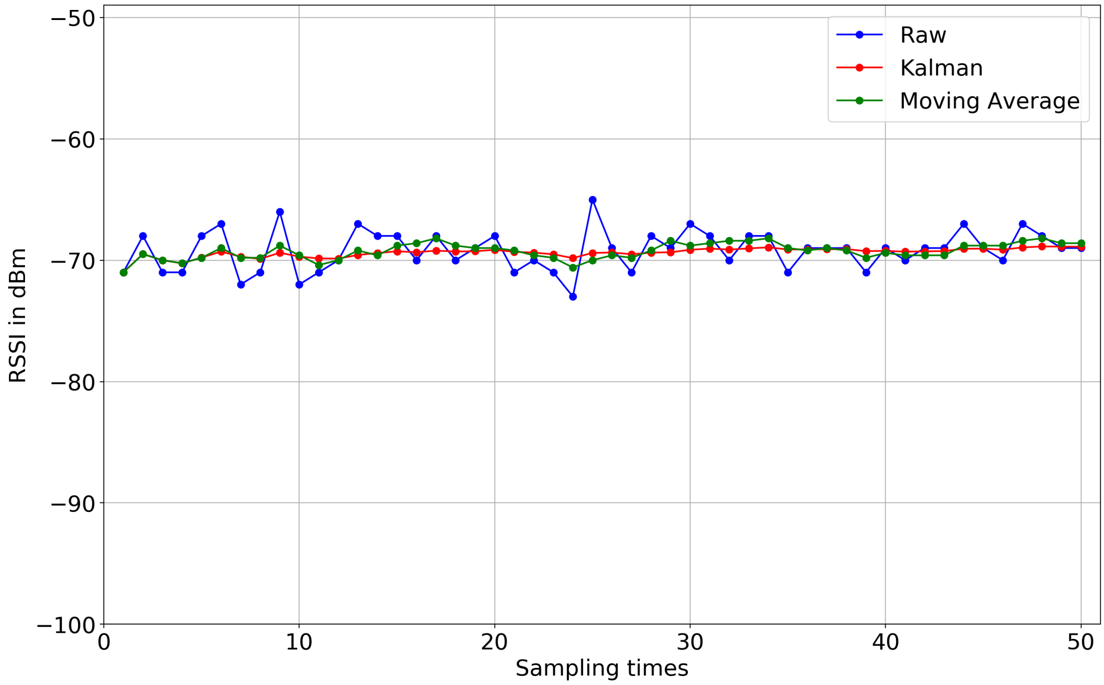


Figure 2.1: RSSI vs Sampling Times

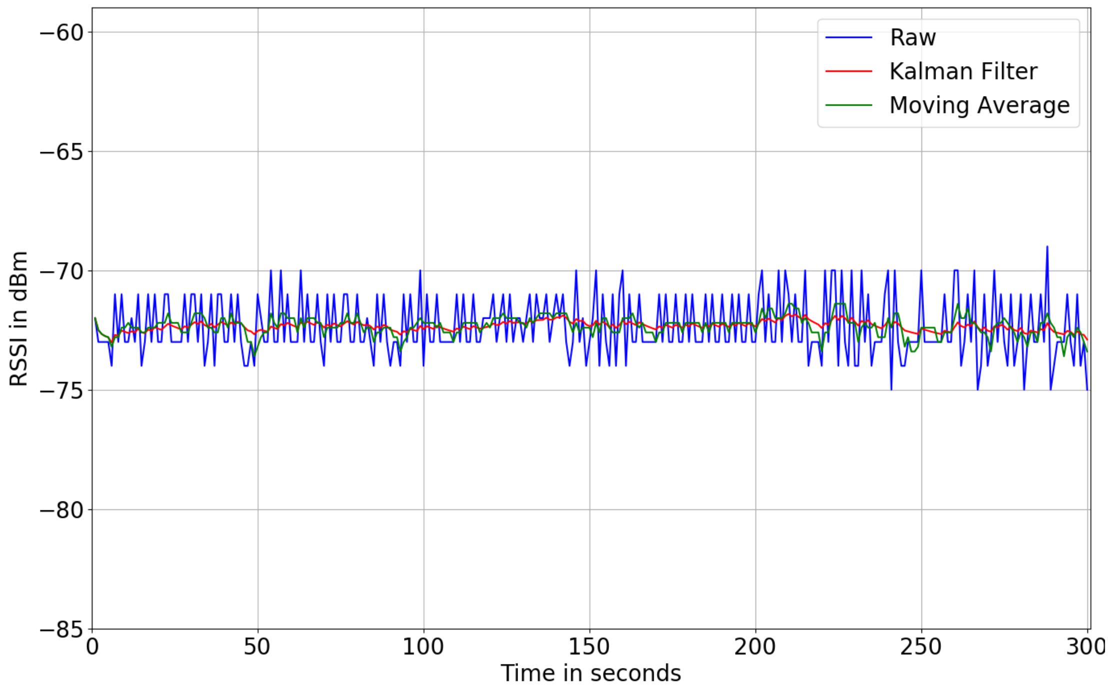


Figure 2.2: RSSI vs Time

2.3 RSSI Distance Model

The distance between the beacon and the receiver can be estimated by the measured RSSI. The logarithmic distance path-loss model is generally used for RSSI distance measurement (Spachos and Plataniotis, 2020). It is expressed as:

$$\overline{RSSI} = -10n\log(d) + \overline{A} \tag{2.1}$$

where $\overline{RSSI}$ is the average measured RSSI, $\overline{A}$ is the average measured RSSI at a distance of 1m from the transmitter, d is the distance between the transmitter and the receiver, and n is a path-loss component depending mainly on the environment.

When solving for the distance:

$$d = 10^{\frac{\overline{A}-\overline{RSSI}}{10n}} \tag{2.2}$$

The RSSI values for BLE beacons are measured at different distances and the parameter n is curve fit to obtain the RSSI distance model for each beacon. The value of $\overline{A}$ for each BLE beacon is fixed separately in each environment.

The value of n will be larger if there are more obstacles (Spachos and Plataniotis, 2020). The accuracy in calculation of path-loss component directly affects the accuracy in estimating the location.

CHAPTER 3

Experiment

3.1 System Model

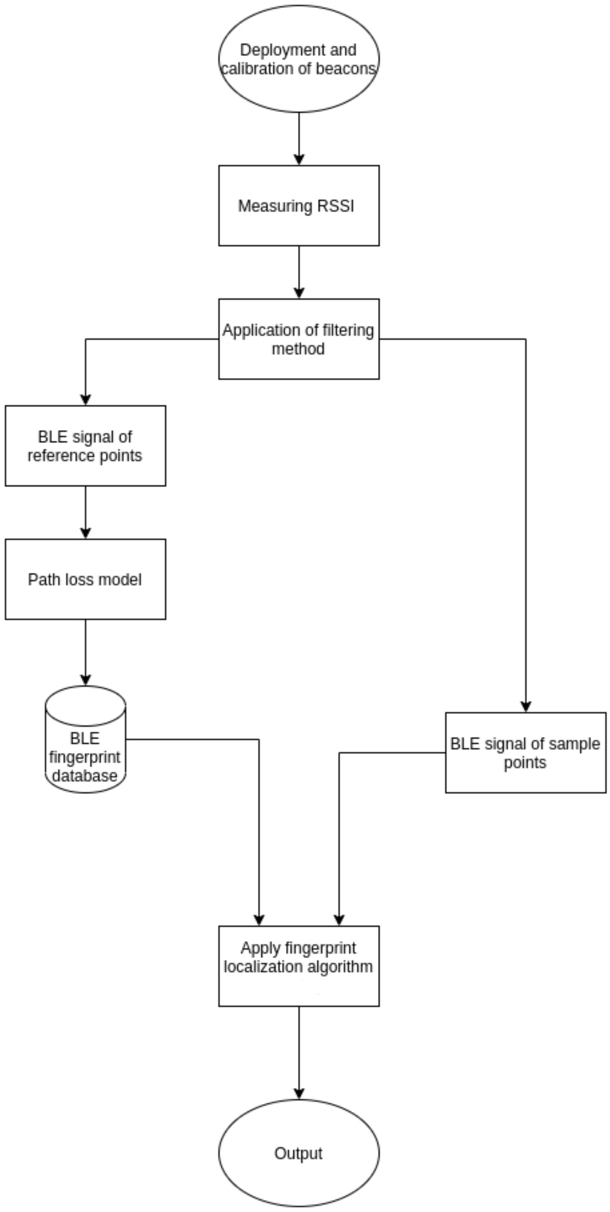


Figure 3.1: Workflow schematic diagram

Based on the workflow schematic diagram in Fig.3.1, we propose the following positioning method:

1. Deploy beacons in the environment and calibrate each beacon separately in each environment.
2. Reference points and sample points are selected. Readings are collected at both the points.
3. The Android application in the smartphone measures the RSSI values taking a time window for the selected points and stores them locally.
4. The RSSI readings are collected from the smartphone, and moving average and kalman filters are applied.
5. RSSI is converted to distance using path-loss model for each beacon using some of the reference point readings.
6. BLE fingerprint database is created that contains average measured RSSI values of the beacons for the reference points and path loss parameters.
7. The position of sample points are estimated using WKNN and NLLS methods.

3.2 Filtering Algorithms

A. Moving Average

In moving average filter, last *n* RSSI samples are measured and then averaged to get a average measured RSSI value. This average value often provides a better representation of the actual RSSI between the transmitter and the receiver. The formula used is as follows:

$$\overline{RSSI} = \frac{1}{n}\sum_{i=0}^{n} RSSI_i \tag{3.1}$$

B. Kalman

One of the most used filters for smoothing RSSI values is Kalman filter. A Kalman filter smooths the values in two stages: prediction and update. In the prediction stage, kalman filter receives a value as input, it compares the input value to the previous value obtained by the kalman filter, and then a new value is estimated and the error between the values is calculated. In the update stage, it updates all the variables for the next calculation. The Kalman filter formulas used are as follows:

Prediction:

Predict the current state:

$$x_k = A * x_{k-1} \tag{3.2}$$

Compute the error covariance:

$$P_k = A * P_{k-1} * A^T + Q \tag{3.3}$$

Update:

Compute the Kalman gain:

$$K = P_k * H^T * (H * P_k * H^T + R)^{-1} \tag{3.4}$$

Compute the new state:

$$x_k = x_{k-1} + K * (Z_k - H^T * x_{k-1}) \tag{3.5}$$

Compute the new error covariance:

$$P_k = P_{k-1} - (K_k * H * P_k) \tag{3.6}$$

where:

Z_k: Measurement vector for current time.

x_k: The current state estimate.

P_k: Estimate of average error for the current state.

A: State transition matrix.

K: Kalman gain.

H: Observation matrix.

Q: Estimated process error covariance.

R: Estimated measurement error covariance.

3.3 Localization Algorithms

A. WKNN

We use a conventional fingerprint matching method for estimating a user's location; the weighted K nearest neighbors (WKNN) method. The Euclidean distance (D_i) between the online collected RSSI value ($\tilde{R}_j$) at the sample point and the stored RSSI value (R_{ij}) at the ith reference point is given by:

$$D_i = \sqrt{\sum_{j=1}^{M} (R_{ij} - \tilde{R}_j)^2} \quad , D_i = [D_1, D_2, \dots, D_N] \tag{3.7}$$

where i is the number of reference points and j is the number of the BLE devices in range ($1 \leq i \leq N, 1 \leq j \leq M$). In this work, we select m beacons for which the RSSI values at the sample point are strongest per reference point in measuring the Euclidean distance (D_i), where m is less than M. The reference points for the computation of the current location are sorted in the ascending order of the Euclidean distances. Then, the first k reference points are selected for estimation of location, where the final location (X_{BLE}, Y_{BLE}) is given by:

$$(X_{BLE}, Y_{BLE}) = \left(\frac{\sum_{i=1}^{i=k} w_i x_i}{\sum_{i=1}^{i=k} w_i} , \frac{\sum_{i=1}^{i=k} w_i y_i}{\sum_{i=1}^{i=k} w_i} \right) \quad , \textit{where } w_i = \frac{1}{D_i} \tag{3.8}$$

where (x_i, y_i) is a coordinate of the ith reference point and w_i is the weight assigned to the ith reference point. The inverse of D_i is used as a weight for respective reference point.

B. NLLS

Given the known positions (x_i, y_i) of the ith beacon, and estimated distances d_i of the receiver device from the ith beacon estimated using RSSI distance model, the position (x, y) of the receiver device can be estimated by finding $(\hat{x}, \hat{y})$ satisfying:

$$(\hat{x}, \hat{y}) = \arg\min_{x,y} \sum_{i=1}^{N} [\sqrt{(x_i - x)^2 + (y_i - y)^2} - d_i]^2 \tag{3.9}$$

where N is the number of beacons that are used to estimate the location of the receiver device. Non-linear least square is an optimization problem with objective of minimizing the sum of the error square (Yang and Chen, 2009).

3.4 Experimental method

The experiments were carried out when there were very less people around to have a stable BLE signal environment.

The advertisement rate was fixed to 1 Hz to not increase the time window of collecting readings. 50 samples per point was collected in a time window of 50 seconds.

If the transmit power of the beacons are set very low, the transmission range of beacons decrease which result in areas having no coverage of beacons (Faragher and Harle, 2015). However, if the transmit power is high, the battery of beacon gets drained faster. We did not consider much about power consumption and fixed the transmit power of beacons to 0 dBm that ensured no isolated regions with no beacon coverage.

An Android smartphone recorded the BLE data to local storage using an application developed by us. During the experiments, a single device was used, and the smartphone holder remained stationary for the time window. The device was held in hand, stable and in front of the holder.

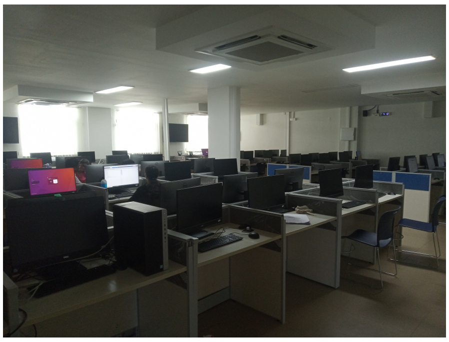
3.5 Experimental testbeds

A. Experimental Environment

We performed the experiments in three testbeds at IITT Transit Campus; Block-C corridor, shown in Fig.3.2a, Computer Centre, shown in Fig.3.2b, and Library, shown in Fig.3.2c. Block-C Corridor covered 64.8 m^2 (36m x 1.8 m), Computer Centre covered 129.96 m^2 (11.4m x 11.4m), and Library covered 146.16 m^2 (17.4m x 8.4m).

The corridor had no obstacles, while the Computer Centre contained cubicles with computers, and library contained book shelves and tables. There was least human obstruction in library. There were times when people walking on the corridor caused obstruction. Computer Centre, for most of the time, had human interference with people moving around and getting in and out throughout the experiment, blocking the LOS of the signal.

(a) Corridor



(b) Computer Centre

(c) Library

Figure 3.2: Experimental environment

B. Beacon deployment

Six beacons were used in corridor with beacon density of 1 beacon per 10.8 m^2, and ten beacons were used in both library with beacon density of 1 beacon per 14.6 m^2 and computer centre with beacon density of 1 beacon per 13.0 m^2. The beacons were mounted on the walls at a height of 1m to 1.5m from the floor, above the obstacles and oriented such that the smartphone which is held parallel to the ground at the same height, gets maximum response.

In each testbed, the beacons were positioned such as to uniformly cover the area. The beacon positions for each testbed are shown in Fig.3.3.

C. Position of reference points and sample points

The reference points were selected for WKNN method such as either they remain close to the beacons or in between large areas left vacant after selecting reference points

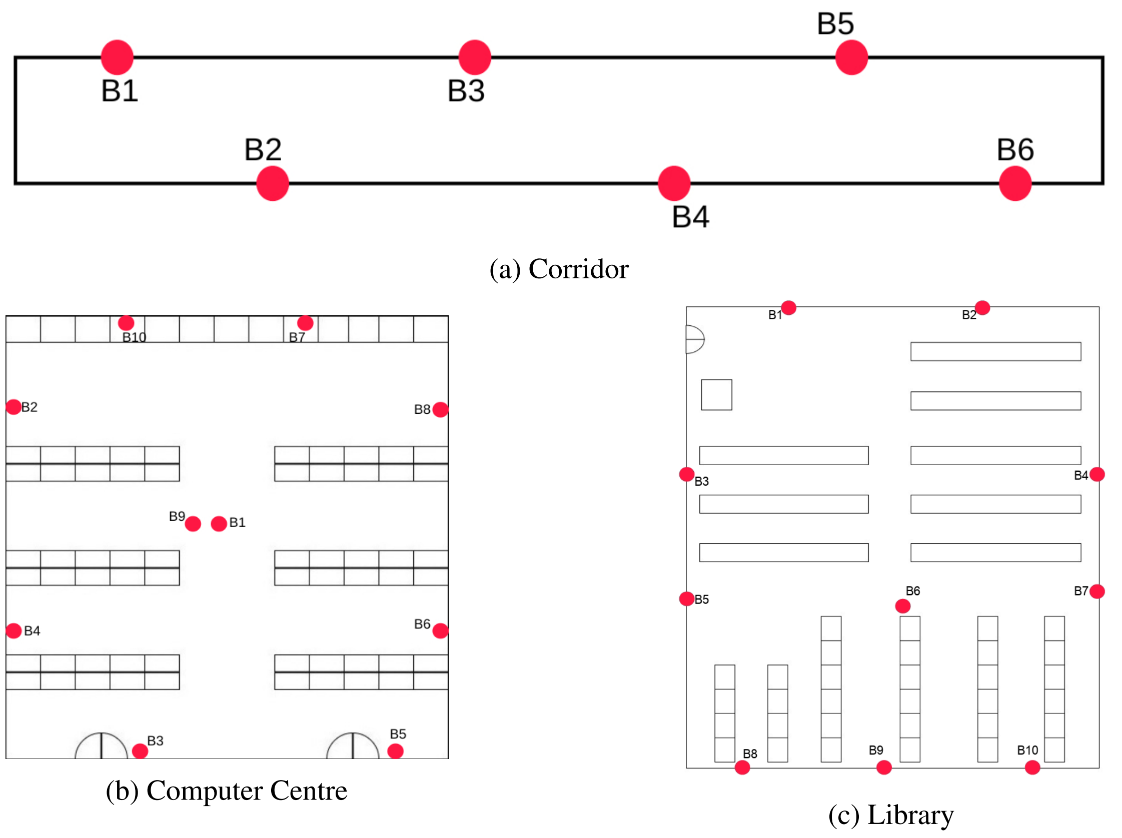
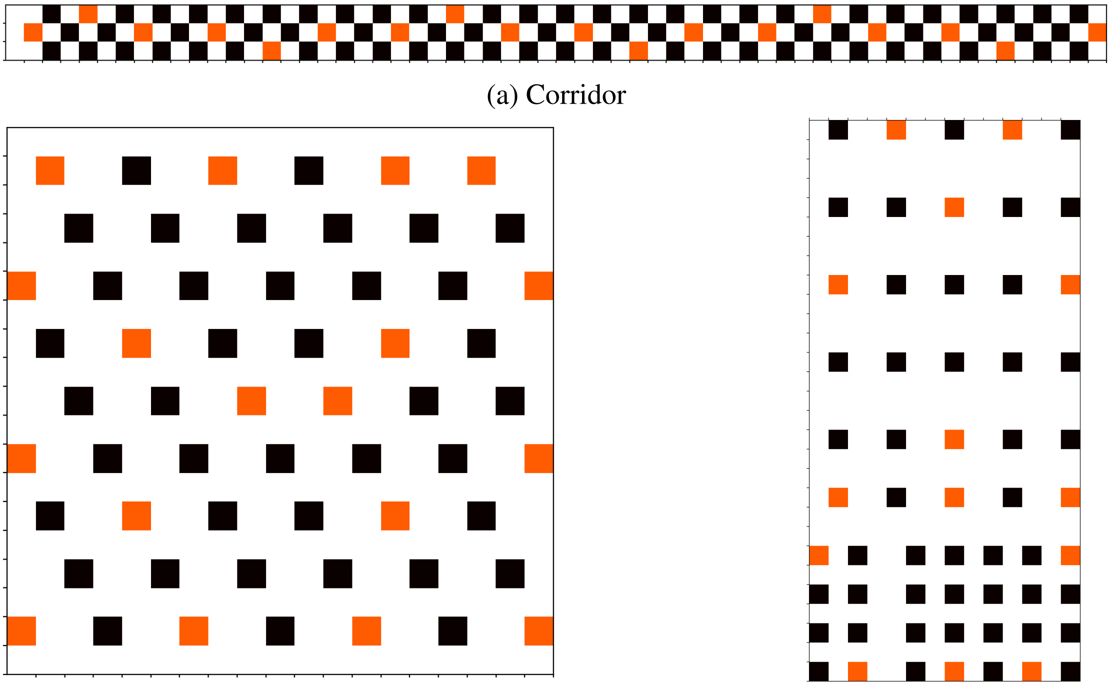


Figure 3.3: Floor plan of testbeds with beacons shown as red dots.

close to the beacons. This was done to have at least three reference points surrounding a sample point within a distance of 5m to achieve good accuracy.

The positions of reference and sample points are shown in Fig.3.4.



(a) Corridor

(b) Computer Centre

(c) Library

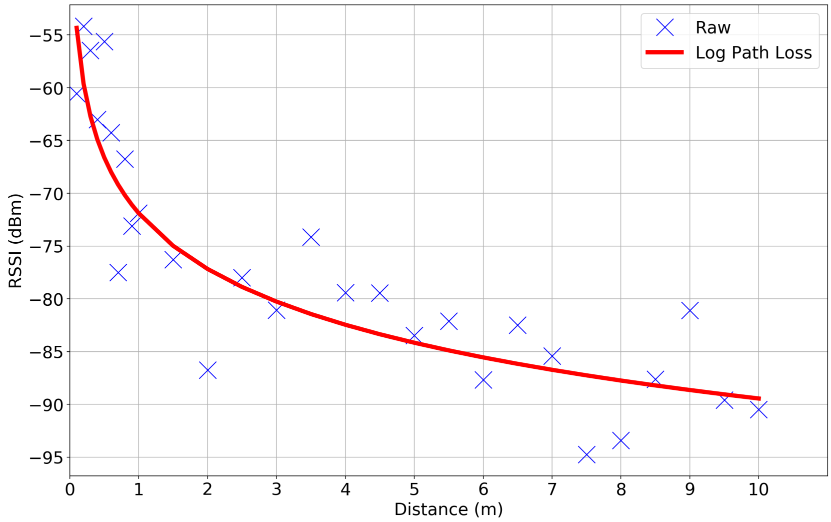
Figure 3.4: Position of reference points and sample points for each testbed with reference points (red) and sample points (black)

3.6 Path Loss Model for different testbeds

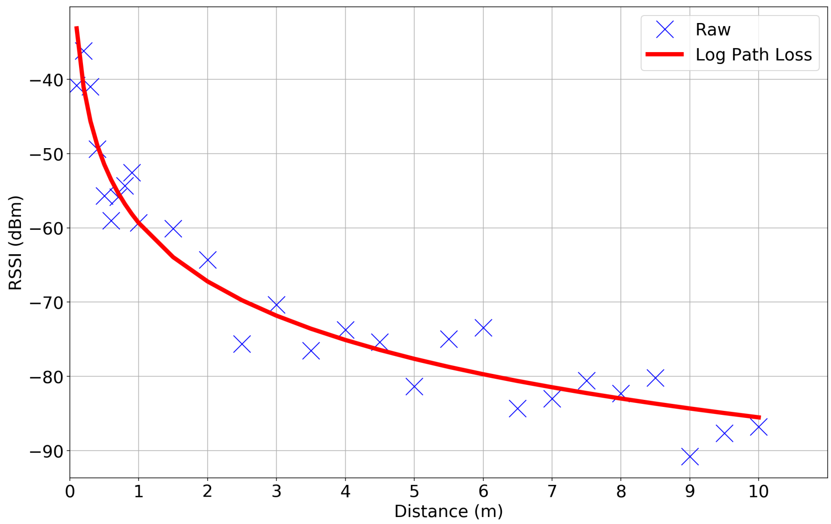
The path loss model was determined at the beginning of the experiment in each of the testbed (Spachos and Plataniotis, 2020). To create the model, the RSSI values were measured over a range of distances in the environment. The RSSI was gathered at twenty eight points, ten between 0 and 1 meter, every 0.1 meters, and eighteen between 1 and 10 meters, every 0.5 meters. The results for one of the beacons in each testbed are shown in Fig.3.5.

RSSI values decrease as the distance of the smartphone from the beacon increases. This is obvious since the signal becomes weaker. An important observation is that the variation increases with distance. The greater variation with distance is due to the weaker signals received that fluctuate due to the obstacles present in between. The probability of meeting obstacle is higher for the farther points than the nearer ones.

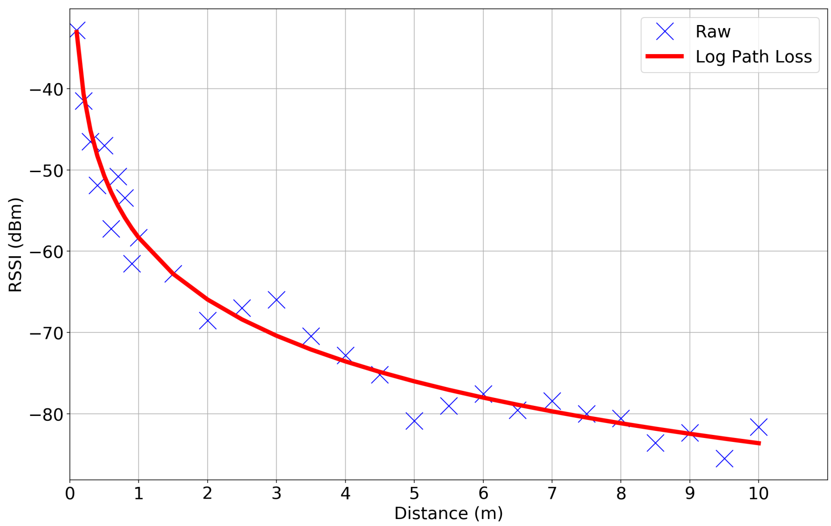
The RSSI values have greater variation in the corridor and the computer centre as compared to the library. The reason for such vaiation is the people walking around in both the testbeds. Hence, it is expected that the accuracy of NLLS method which relies on path loss model is less for the corridor and the computer centre.



(a) Corridor



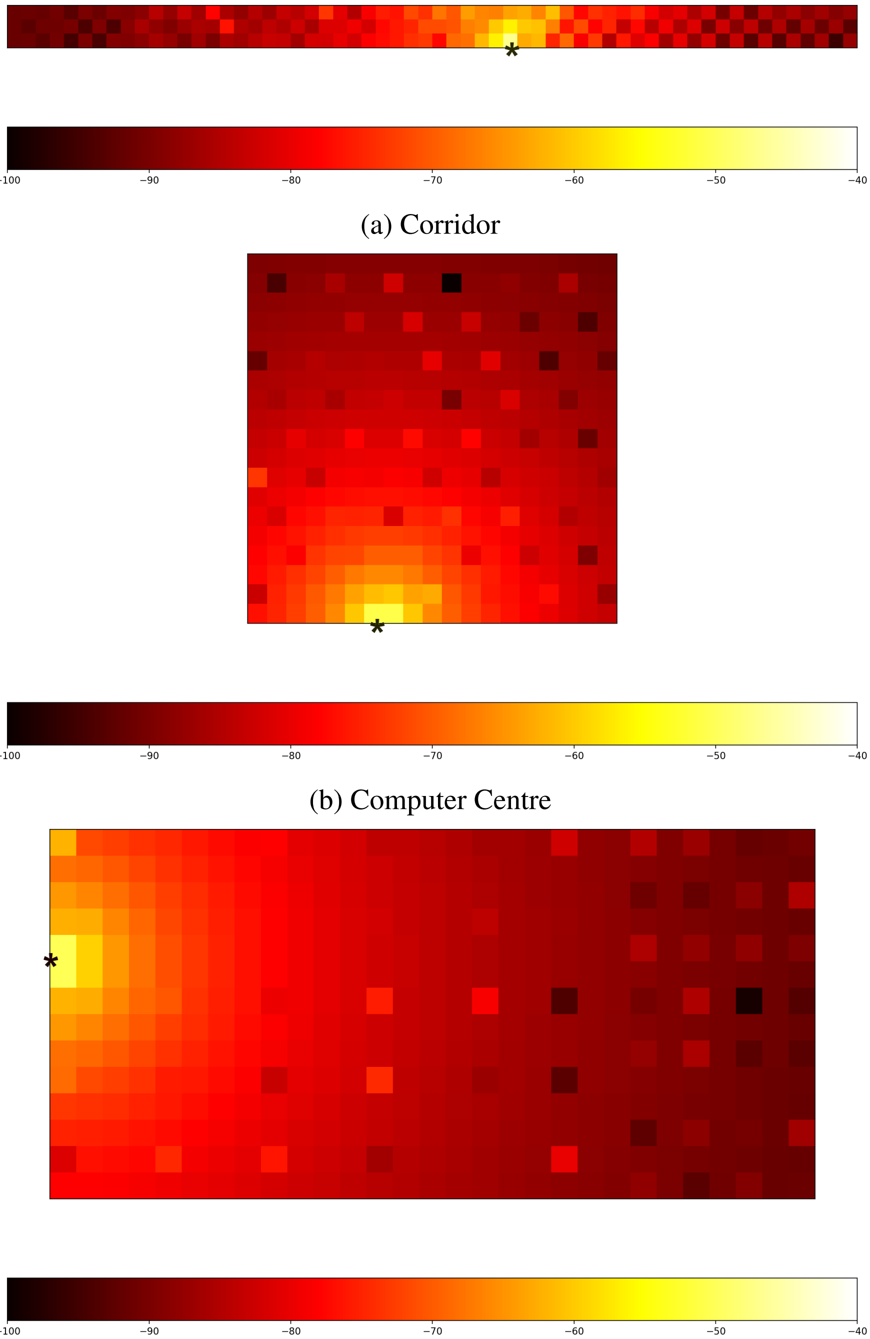
(b) Computer Centre



(c) Library

Figure 3.5: Curve fitting for the path loss

We used the path loss model to generate a signal strength map for each beacon in an experimental environment. The results for one of the beacons in each of the testbed are shown in Fig.3.6 .



(a) Corridor

(b) Computer Centre

(c) Library

Figure 3.6: BLE signal strength map with beacon position shown as black *

CHAPTER 4

Results and Discussions

4.1 Evaluation metrics

The evaluate the outputs, we used two evaluation metrics commonly used in the indoor localisation: Mean Absolute Error (MAE), and Maximum Error. We mainly focused on reducing MAE and getting more number of points under a MAE of 1m. We calculated these errors for all combinations of filtering method, localisation algorithm, number of reference points, and fingerprint dimensionality. The summary of best results obtained from varying all the parameters mentioned, are reported in the next section.

4.2 Summary of best errors

Two different filter methods were used: moving average, and Kalman. For each of the filtering methods, two different localization techniques are used : WKNN and NLLS with varying fingerprint dimensionality. k (Number of reference points) is varied in WKNN. A summary of the best errors obtained for each of the filtering methods and localization techniques can be seen in Table 4.1 for the corridor, Table 4.2 for the computer centre, and Table 4.3 for the library. Raw filter in the above mentioned tables means no filter was used.

The highest value of maximum error obtained was 6.34m for the computer centre with kalman filter and NLLS method. The maximum error for each of the testbeds, for other combinations of the parameters given in the table was under 6m, which is good for indoor localisation using NLLS and WKNN (Sadowski and Spachos, 2019).

We obtained best MAE of 1.11m for the corridor with moving average filter and WKNN method. Best MAE of 1.59m for the computer centre was obtained with raw filter and WKNN method. For the library, we obtained best MAE of 1.16m with raw filter and NLLS method. As it is evident from the tables, that filtering method did not greatly affect the values of error obtained in each of the testbed. The results are very similar on varying filtering method for a particular testbed and localisation technique.

Table 4.1: Summary of best errors obtained for Block-C Corridor

Filtering Method	Localization Technique	Mean Absolute Error(m)	Maximum Error(m)	Fingerprint Dimensionality
Raw	WKNN	1.13	2.68	6
	NLLS	1.82	5.17	6
Moving Average	WKNN	1.11	2.74	6
	NLLS	1.85	5.32	6
Kalman	WKNN	1.12	2.82	6
	NLLS	1.87	5.32	6

Table 4.2: Summary of best errors obtained for Computer Centre

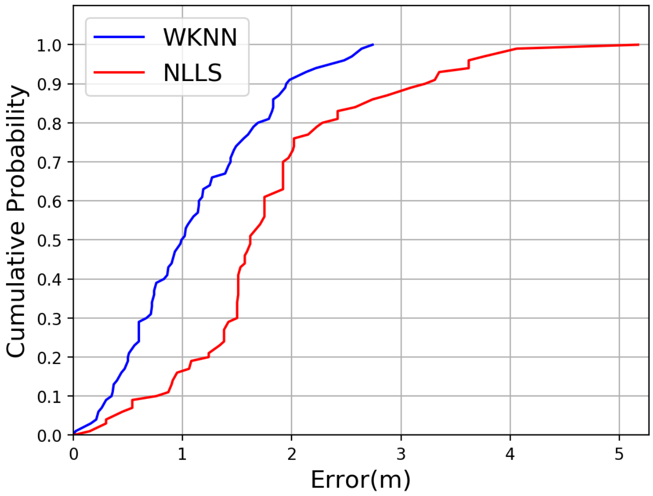
Filtering Method	Localization Technique	Mean Absolute Error(m)	Maximum Error(m)	Fingerprint Dimensionality
Raw	WKNN	1.59	5.86	10
	NLLS	1.71	5.79	4
Moving Average	WKNN	1.61	4.77	10
	NLLS	1.71	5.89	4
Kalman	WKNN	1.63	5.84	10
	NLLS	1.76	6.34	4

Table 4.3: Summary of best errors obtained for Library

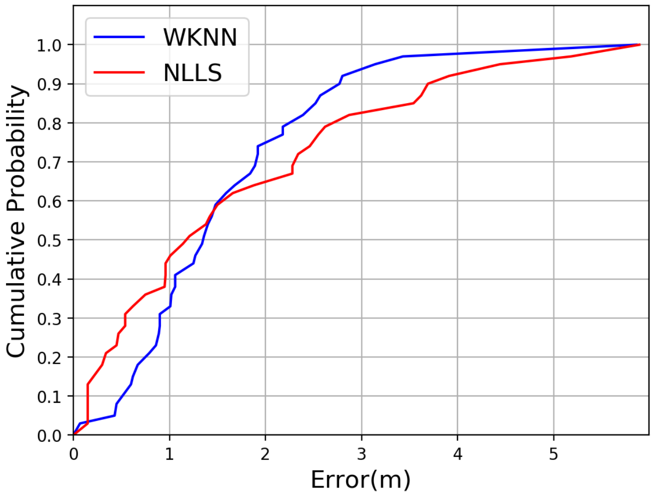
Filtering Method	Localization Technique	Mean Absolute Error(m)	Maximum Error(m)	Fingerprint Dimensionality
Raw	WKNN	1.69	3.92	10
	NLLS	1.16	5.79	5
Moving Average	WKNN	1.68	3.93	10
	NLLS	1.21	5.95	4
Kalman	WKNN	1.67	3.93	10
	NLLS	1.19	5.64	3

However, the localisation technique had an effect on best error obtained in each testbed. Using WKNN method instead of NLLS, for moving average filter in the corridor, as seen in Table 4.1, improves the MAE by 0.74m or 40%. As seen in Table 4.2, using WKNN method instead of NLLS, for raw filter in the computer centre, does not produce much improvement. The MAE improves by only 0.12m or 7.5%. For the library, using kalman filter with NLLS, improves MAE by 0.53m or 31.4%. While WKNN generated least error in the corridor and the library, least error in the library was achieved using NLLS method. This is expected because there was more variation in RSSI values for the corridor, and the computer centre than the library, which resulted in not so accurate path-loss model for the corridor, and the computer centre, while more accurate path-loss model for the library. Moreover, the density of reference points, as seen in Fig. 3.4 was maximum in the corridor among the experimental environments, which increased the accuracy of WKNN method for the corridor. An important observation here is that, for an environment like corridor where one of the dimensions of the testbed is small while the other one much greater, the reference points should be arranged keeping in mind that the longer dimension will contribute more to the error. So, the error along the greater dimension should be minimised.

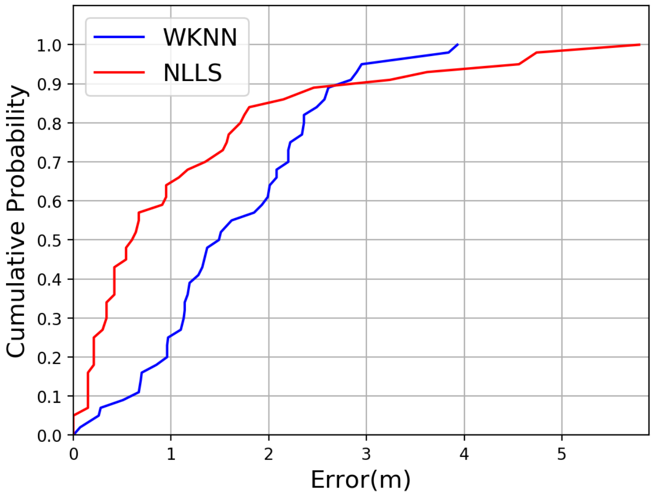
From the cumulative probability graphs given in Fig.4.1, it is evident that the performance of NLLS method improves from the corridor to the library. In the corridor, for WKNN, 90% of the points were predicted with MAE of less than 2m, while only 75% of the points had MAE under 2m in NLLS. The WKNN and NLLS performed equally well in the computer centre. The NLLS method proved to be the winner in the library with more than 65% of points under an MAE of 1m, while in WKNN method, only 25% of the points had MAE under 1m.



(a) Corridor



(b) Computer Centre



(c) Library

Figure 4.1: Cumulative probability of error

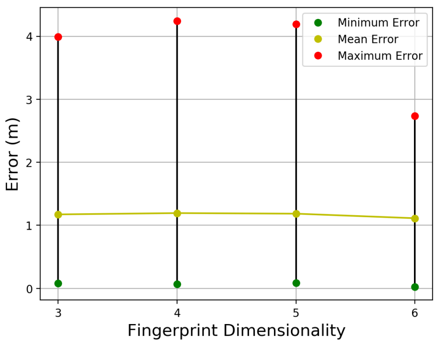
4.3 Impact of fingerprint dimensionality

In this section we study the effect on MAE, varying fingerprint dimensionality for each testbed with WKNN and NLLS algorithm.

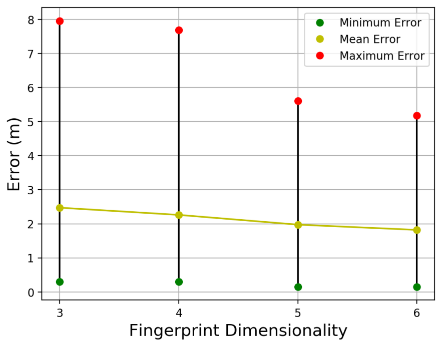
From Fig.4.2a, Fig.4.3a, and Fig.4.4a, it is observed that as the fingerprint dimensionality increases from 3 to the maximum number of beacons used, the MAE first increases but finally drops to the least value at maximum number of beacons used.

From Fig.4.2b, Fig.4.3b and Fig.4.4b, it is observed that although, increasing fingerprint dimensionality reduced MAE in the corridor, different pattern was seen for the other two environments. In the computer centre, and the library, the MAE decreases, attains the least value and then increases as the fingerprint dimensionality increases.

From Fig.4.2, Fig.4.3, and Fig.4.4, it can be seen that fingerprint dimensionality that produces minimum MAE for one of the localisation technique does not necessarily produce minimum MAE for the other technique. In all the testbeds, for both the techniques, MAE is least for different fingerprint dimensionalities.

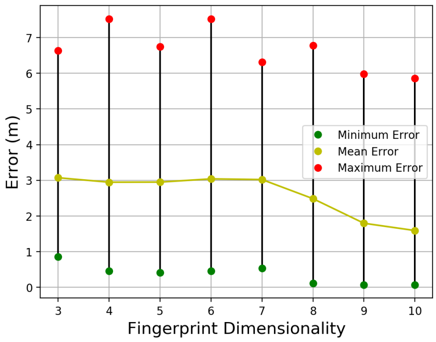


(a) WKNN

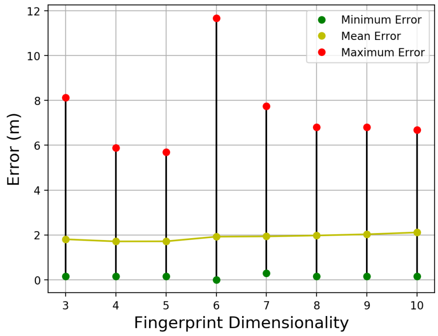


(b) NLLS

Figure 4.2: Localisation Error with fixed filtering method for different types of localisation techniques for Corridor

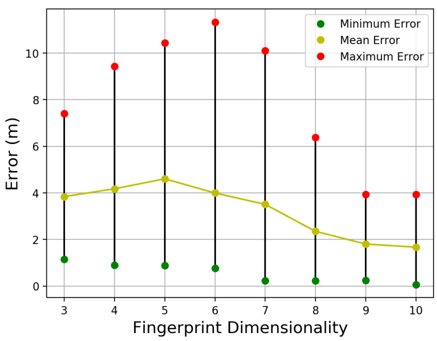


(a) WKNN

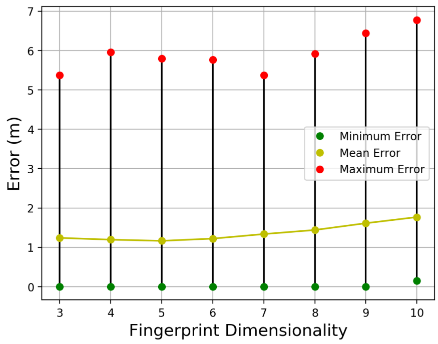


(b) NLLS

Figure 4.3: Localisation Error with fixed filtering method for different types of localisation techniques for Computer Centre



(a) WKNN



(b) NLLS

Figure 4.4: Localisation Error with fixed filtering method for different types of localisation techniques for Library

CHAPTER 5

SUMMARY AND CONCLUSION

The experimental results revealed insights about the localisation technique, and fingerprint dimensionality that can be used for different types of environment. A relation of fingerprint dimensionality with the type of localisation technique was obtained. In order to get good accuracy, we just can not keep increasing beacons as there would be interference. In each of the testbed, beacons were deployed uniformly so that there is no blind spot or any uncovered region. We have taken many sample points to test the accuracy of this system.

We experimented on testbeds with area as small as 65 m^2 to as large as 146 m^2. If the testbed is crowded, we observe MAE goes up as it happened in computer centre as there was less LOS communication between receiving device and transmitting device. The error in such an environment may be reduced using fusion of other technologies such as magnetic field, light intensity, and other smartphone sensors.

In this paper, through experimental results we find NLLS algorithm works better as compared to WKNN, except for the environments where path loss is very high.

Further work is needed to evaluate the trends observed in the fingerprint dimensionality for highly variable environments such as retail places. The fingerprint complexity decreases in such places as the beacon density is less. Improved filtering method like extended kalman filter can be applied in order to remove noise in the RSSI values.

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