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Chapter 9

Artificial Intelligence for localisation of Ultra-Wide Bandwidth (UWB) sensor nodes

Fuhu Che[1], Abbas Ahmed[1], Qasim Zeeshan Ahmed[1] and Muhammad Zeeshan Shakir[2]

The application of position- or location-awareness is becoming more and more prominent and the demand for indoor positioning system (IPS) is urgent. Many different wireless technologies have been employed for the development of IPS, such as Bluetooth, Radio Frequency Identification (RFID), Zigbee, Ultra-Wide Band (UWB), WiFi, etc. Among these different technologies, UWB has a unique advantage in penetration ability, precise ranging, anti-multipath and anti-interference due to it has extremely large bandwidth. However, factors such as environmental noise, multipath effect, interference of nearby devices, non-line of sight (NLOS) environment etc. affect the accuracy of positioning and localisation. Therefore, in this chapter, we attempt to enhance the indoor positioning accuracy of the UWB system by developing a Naive Bayes (NB) classifier. Root Mean Square Error (RMSE) criterion is selected to classify the received data into three different levels; low, medium, and high accuracy. After that, receiver operating characteristics (ROC) curves are plotted and the area under the curves (AUC) enables us to visualize the accuracy of NB classifier. The developed technique is then tested and verified by two different indoor scenarios. The IPS is initially tested in a small-sized room having an area of around $16m^2$, followed by testing in a medium-sized room having an area of around $26m^2$. From our

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measurements, the NB classifier can achieve more 90% accuracy in the LOS environment and more than 87% of accuracy in a partial LOS environment.

1. Introduction

Positioning defines the ability to determine where an object or a person is located [1]. In recent years, the Global Positioning System (GPS) has brought great convenience to people's daily life, such as travel and navigation. In 2017, the United States government claimed that with the help of GPS technology, the range of location error for an average user is within 7.8m with 95% confidence interval [2]. However, this accuracy will not be suitable for an indoor localisation application where the GPS signals are blocked. An indoor positioning system (IPS) will continuously determine the position of a person or an object in real-time with high accuracy [3]. Furthermore, the environment of indoor is challenging, because of different floor layout, non-availability of line-of-sight (LOS) path, multipath due to the presence of different materials, and further complex and unknown environments. Ultra-wideband (UWB) is a suitable approach for IPS due to its extremely short radio pulses and wider frequency bandwidth that can facilitate the signal to pass through obstacles effectively and reduce infinite time resolution led by multipath effects [4]. UWB can provide centimeter-level positioning accuracy and can co-exist with existing RF signals or external noise like WiFi and Bluetooth low energy (BLE) due to the high data rate of communication.

There are several different positioning UWB algorithms positioning can be classified into three main categorisations that are the time of arrival (TOA) [5], time difference of arrival (TDOA) [6] and Two-way ranging (TWR) [7]. The principle is to install anchors or beacons at a known position and then to calculate the exchange of UWB signals between those known anchors and tags or agents with unknown position [8]. From this and the known positions of the anchors, the tag can then be localised by doing multilateration methods [9]. Each algorithm needs more than three anchors to locate the position of a tag in two-dimensional (2D) environment and more than four anchors to locate the tag in three-dimensional (3D) environment [10]. However, all these algorithms can detect within 10cm of accuracy in LOS environment, which is superior to the other detection techniques such as WiFi, BLE and GPS.

This positioning accuracy within 10 cm is sufficient for general environments, but for some special occasions, like a moving forklift truck in a warehouse, this accuracy needs to be further improved as it may cause severe injury to the workers in the warehouse. Furthermore, UWB transmit power spectral density requirement is under -41.3dBm/Hz which limits the coverage distance [11]. The maximum distance with this power spectral density is generally less than 100m [12]. As this coverage distance is a big problem so, when employing UWB systems for an indoor area such as airports, large factories, shopping malls, and stadiums, etc., a large number of anchor nodes will be required, as a result the cost of the deployed system will be increased. At present, most of the positioning accuracy algorithms require a clear LOS between the anchors and the tags. The accuracy of the algorithms is greatly reduced when this LOS is not there [13]. Therefore, maintaining high-precision positioning in Non-Line-of Sight (NLOS) will be an immense challenge [14]. With keeping with these challenges, localisation algorithms are urgently required where the accuracy is still maintained when moving with fast speed, covering large distances and in NLOS environments.

Artificial Intelligence (AI) is constantly evolving and currently knows no bounds. The power of Machine Learning (ML) is ensuring that the limits of AI bounds are extended and the rules of traditional programming are broken. The deployment of AI and ML has already been proposed in various standards, including the 3rd Generation Partnership Project (3GPP) network data analytics (NWDA) [15], and the European telecommunications standards institute (ETSI) experimental network intelligence (ENI) [16]. NWDA utilises the approach of slice and traffic steering and splitting, while ENI uses a cognitive network management architecture and context aware-based approach [17]. This chapter employs a similar approach to AI and ML for improving the UWB positioning for LOS and NLOS environments. We propose a Naive Bayes (NB) classifier, which employs a probabilistic machine learning (ML) approach to the UWB positioning data. NB is preferred over other techniques because of its easy scalable quality and for the ability to respond to the request instantaneously. The collected data is classified into three different categories depending upon their distance from the exact location, which is low, medium and high. The IPS is first tested in a small-sized room having an area of around $16m^2$, followed by testing in a medium-sized room having an area of around $26m^2$. From our measurements, the NB classifier can achieve more 90% accuracy in Line of Sight (LOS) environment and more than 87% of accuracy in partial LOS environment. Receiver operating characteristics (ROC)s are then employed to help visualise the proposed classifier and to evaluate the usefulness of the ML technique. The ROC curve indicates that the area under the curve (AUC) is 96.2% and 93.1%, respectively for high accurate samples when measurement is carried out in small- and medium- sized room.

This chapter contribute in following two ways:

i. A ML based NB classifier is developed to improve the positioning and localisation capability of the IPS.
ii. An extensive experiment is carried out based using UWB sensor nodes for two different sized rooms. Furthermore, LOS and partial LOS scenarios are studied in detail.

In the remaining of the chapter, we review and compare the various positioning technologies available. As our focus is towards the UWB system, we briefly discuss the three IPS techniques, which are TOA, TDOA, and TWR. In section 3, UWB ranging accuracy is evaluated by employing the NB classifier. ROC is also discussed in this section. In section 4, the developed UWB IPS are evaluated with NB classifier and ROC, followed by experimental setup and results. Finally, the chapter is concluded in section 5.

2 Indoor Positioning System (IPS)

2.1 Technologies for localisation

Several technologies have been employed for IPS such as Radio Frequency Identification (RFID), WiFi, Bluetooth, UWB and Zigbee [18]-[19]. However, when deciding about the appropriate IPS technology a judicious balance between the system complexity, cost, and accuracy is required. RFID, WiFi, and Bluetooth have gained much attention due to its advantages in terms of low cost and ease of deployment. These techniques mainly employ the radio signal strength indicator (RSSI) to localise the target objects. The distance between the receiver and object is calculated through the attenuation of radio waves are proportional to its distance. However, the main challenge is the performance in the presence of multipath propagation, interference, and localising multiple objects, among others. Different approaches such as tag-, reader-, or hybrid-based have been incorporated for the purpose of localisation and positioning. Table 1, summarizes the comparison of these different positioning technologies mentioned in terms of accuracy, coverage area, battery lifetime, number of tags required and price and so on. However, as we are more focused towards localisation and accuracy is a key requirement, in this chapter our focus is towards UWB system for IPS.

Table 1: Comparison different positioning technologies

	RFID	Wifi	Bluetooth	UWB
Accuracy (m)	<3 [20] [21]	<15 [22]	<10 [23]	<0.1 [25][26]
Coverage area (m)	<100 [20][21]	<10 [22]	<50 [24]	<20 [25][26]
Battery Lifetime	Years [18]	Weeks-Months	Years	Days-Months depending upon duty cycle
Number of tags	Low	High	High	Low-High
Stability of the large area	Medium	Medium	Medium	Complex
Cost	Low	Medium	Medium	High

2.2 UWB IPS

Different UWB positioning algorithms have been developed in the literature. These algorithms can be classified into three main categories, which are TOA, TDOA, and TWR. Let us now discuss these algorithms in details.

2.2.1 Time of Arrival (TOA) positioning system

In Time Of Arrival (TOA) positioning system, the transmitter and the receiver are time synchronised. Time of arrival or sometimes called as time of flight evaluates the travel time from the transmitted to a remote receiver. The distance is measured by using the round-trip time and then multiplying it by the speed of light. Now trilateration techniques can be employed for determine the exact location of the tag. There are many algorithms for trilateration in literature such as [26]-[28] and references therein. Trilateration is a process of determining the relative position of the tag utilising the geometry of triangles. In this method the distance, two or more anchors are required to measure the distance between the tag and the anchors. Therefore, if we know the position of the anchors, the above can help us calculate distance d1, d2, and d3 as depicted in Figure 1.

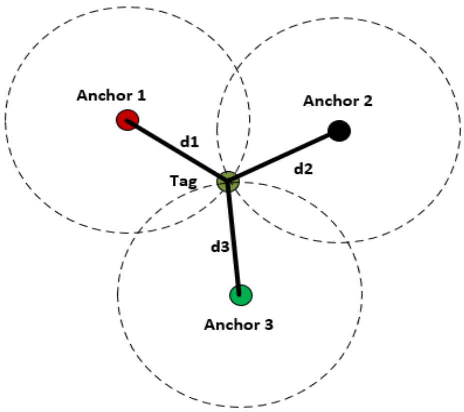

Figure 1: TOA positioning algorithm model

The distance in 2D between target and reference node di is calculated by the following formula

$$d_i = \sqrt{(x - x_i)^2 + (y - y_i)^2} = c(t_i - t), \qquad i = 1,2,3, \dots, \qquad (3)$$

where x and y are the coordinates of the target or tag, x_i and y_i are the coordinates of the reference node or anchor i. Therefore, the target can be uniquely localised at the intersecting point of these three circles as shown in Figure 1. The TOA algorithm requires accurate synchronisation as a small-time error will have a devastating impact on the position accuracy. This project will use the TOA algorithm, as it is simple and the algorithm improves the battery life of the nodes. However, this algorithm requires all tags and anchors to have the same reference clock.

2.2.2 Time Difference of Arrival (TDOA) positioning system

If the transmitter and the receiver cannot reach time synchronisation, the Time Difference Of Arrival (TDOA) algorithm is a better choice. TDOA calculates the time difference of arrival of a signal sent by an object and received by three or more anchors. The distance in 2D between target and reference node di is represented by the following equation

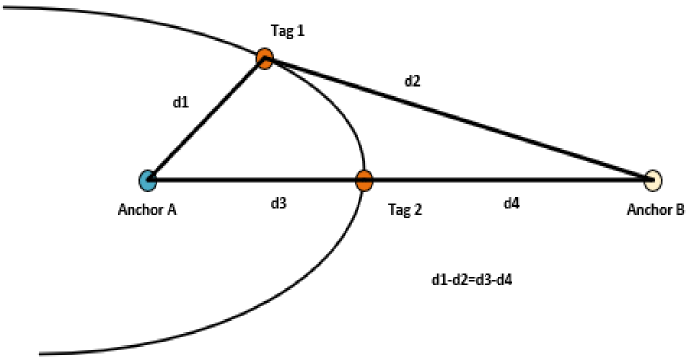

Figure 2: TDOA positioning algorithm model

$$t_{AB} * c = d_1 - d_2 = d_3 - d_4 = \sqrt{(x - x_A)^2 + (y - y_A)^2} - \sqrt{(x - x_B)^2 - (y - y_B)^2}, \quad (4)$$

where, t_{AB} represents the TDOA between reference Anchor A and Anchor B as shown in Figure 2, $c$represents the speed of light, $x$and y are the coordinates of the target. (x_A, y_A) and (x_B, y_B) are the coordinates of reference anchor A and B, respectively. More than four reference anchors are required to estimate the target location in 2D environment. The challenge of TDOA-based approaches is significant requirement of the bandwidth compared with other algorithms and at least four anchors.

2.2.3 Two-Way Ranging (TWR) positioning system

The distance between an anchor and a tag can be calculated by utilising the two-way-ranging (TWR) technique when there is no common clock among reference nodes. TWR technique algorithm utilizes bidirectional messages exchanged between a target and a reference node. Time elapse from transmitting a message to receiving its response is required for the TWR calculation. Apart from these algorithms. There are several other algorithms to use such as: RSSI, angle of arrival (AOA) and hybrid algorithm. These algorithms need to be selected according to the design requirement and circumstances. However, developing algorithms which improves UWB positioning and localisation capabilities is still an active area of research [30]-[33].

3. UWB Ranging Accuracy Evaluation

As we discuss the positioning mentioned above, all the algorithms are based on the measurement of time standards. In this case, there will be some time deviations or frequency deviations caused by the radiator directly or caused by the multipath and NLOS scenarios. In this way, the calculated position will deviate from its true position, resulting in extremely low positioning accuracy at some time points which will greatly affect the accuracy of overall positioning. Therefore, the detection of outliers is the key to determine the accurate overall positioning system. Naïve Bayes can be used to evaluate the accuracy of system positioning and the ROC curve can be used to visually observe the performance of the positioning. This section is going to analysis the characteristic of Naïve Bayes and the ROC curve.

3.1. Naive Bayesian (NB) classifier

Naive Bayesian (NB) classifier is one of the most popular and widely used classification algorithms in machine learning (ML). In this method, Bayesian principle is employed which deploy probability statistics on the sample data set. From the probability perspective, according to Bayes Rule, the given probability $P(l|x)$can be measured as

$$P(l|x) = \frac{P(x|l)P(l)}{P(x)}, \tag{5}$$

where $P(l|x)$ is the probability of location given the distance of the anchors. $P(l)$is the prior probability of the location or position.$P(x|l)$ is the probability of the distance given location and the $P(x)$is the prior probability of the distance of the anchors.

As discussed above location-aware network has two types of sensor nodes. Anchors or beacons are nodes with known position, while tags or agents are nodes whose position is unknown. We focus on a network with total N number of anchor nodes and a tag which position we want to determine. The Euclidean or the exact calculated distance between the tag and the i-th anchor is given as $d_i, i = 1,2, \dots, N$ and the estimate distance between the i-th anchor and the UWB tag is given as $\hat{d}_i, i = 1,2, \dots, N$. Now NB can be used to classify the collected data which is received from the anchors. Root Mean Square Error (RMSE) is the arithmetic square root of the mean squared error. The mean squared error is the average of the square of the difference between the measured distance and the actual distance. Therefore, RMSE is a measure of the deviation between the observed and the true value. The RMSE calculation formula is shown below

$$\boldsymbol{RMSE = \frac{1}{N}\sqrt{(d_1 - \hat{d}_1)^2 + (d_2 - \hat{d}_2)^2 + \cdots + (d_N - \hat{d}_N)^2}}\ . \qquad (6)$$

Table 2 below shows an IPS when four anchors and a tag are employed. However, it is difficult to intuitively evaluate the overall IPS because of a large data set. The three different levels of classifier are decided with the help of (6). If RMSE value is between $0 \leq RMSE < 0.03$, the data is classified as having high positioning accuracy, for a RMSE value of $0.03 \leq RMSE < 0.05$, the data is classified as having medium positioning accuracy, and finally, when the $RMSE \geq 0.05$, the data is classified as having low positioning accuracy. Keeping in view, with the above threshold the Table 2 data is classified as having low, medium or high accuracy positioning information.

Table 2: Classification of the IPS according to RMSE

Anchor-1		Anchor-2		Anchor-3		Anchor-4		RMSE	Classification Level
d_1	$\hat{d}_1$	d_2	$\hat{d}_2$	d_3	$\hat{d}_3$	d_4	$\hat{d}_4$		
3.03	2.94	1.77	1.99	2.88	2.8	1.9	1.85	0.0639	Low
3.03	2.95	1.77	1.73	2.88	2.8	1.9	1.88	0.0304	Medium
3.03	3.04	1.77	1.77	2.88	2.84	1.9	1.89	0.0106	High

3.2 Receiver Operating Characteristic (ROC)

While the Naïve Bayes (NB) algorithm is used to classify the results of the system, receiver operating characteristic (ROC) enables a visual plot showing the performance of the classifier using a different threshold value. The ROC curve was initially used in World War II for evaluating the radar signals before deploying it in signal detection theory [14]. It is created by plotting the true positive rate (TPR) against the false positive rate (FPR) at numerous threshold settings. TPR determines how many correct positioning results occurred among all the positive positioning results available during the test. While, FPR, defines how many incorrect results have occurred among all negative positioning results available during the test.

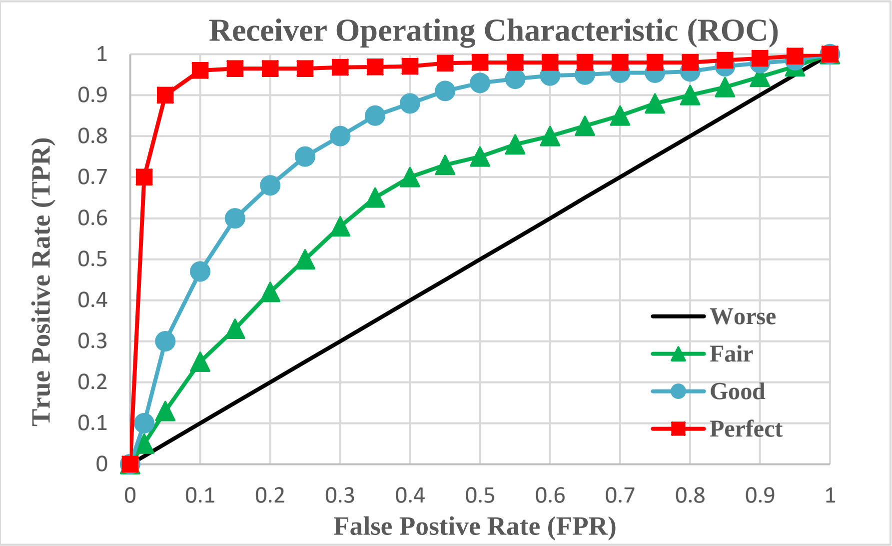

Figure 3: Receiver Operating Characteristic (ROC) curve

The accuracy of classifier can be measured by determining area under the curve (AUC). Generally, the more the AUC the better the classifier. An area of 1 shows the classifier has a perfect result, while an area of 0.5 represents a worse test which means the classifier cannot separate the samples for testing. Figure 3 illustrates the performance of the classifier and depending upon the AUC, it is classified into four different categories. The black curve indicates that the classifier does not have the ability to separate the samples, while the red curve indicates that the classifier is able to separate the samples accurately. Let us now proceed towards the implementation and evaluation of our UWB IPS system.

4. Implementation and Evaluation

In this section, we will mainly describe how the NB classifier algorithm and ROC curve are applied to the IPS to evaluate the system performance. Figure 4 illustrates the block diagram of the developed IPS system. The system operates by employing two phases: offline training and online testing. In the first phase, which is the training phase the IPS data is collected from the tag and pre-processed. The distance between the anchors and tags is calculated, followed by the RMSE as mentioned in (6). It is further used to produce the fingerprint library. During the testing phase, the IPS data are calculated and pre-processed. They are then compared with the database utilising an NB classifier as mentioned above. The ROC is then plotted and the confidence level is calculated which is utilised to improve the positioning results by deriving the final estimated location of the tag.

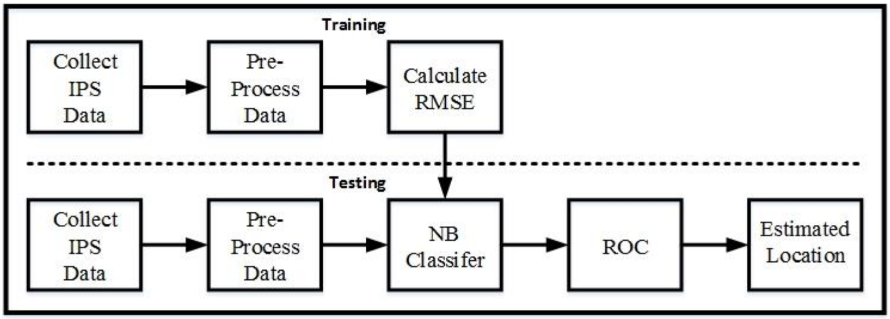

Figure 4: Block Diagram of developed IPS system

As mentioned previously there are two stages for the NB classifier, which are offline training followed by online testing, respectively. As depicted in Algorithm 1, during the training phase, the data is collected, pre-processed and then the distance between the tag and the anchors are estimated. As the position of the user is known, therefore, RMSE can be used to classify that data into three categories such as high, medium and low accuracy. In this training stage, the original distances are classified and based on the subsequent fingerprints are collected and combined as a fingerprint.

Classifier: Offline Training Stage:

Require: Dataset of the area
Require: Determine the distance
    for each location i
        calculate the distance of tag from each anchor
    end
Calculate **RMSE**

Classifier: Online Testing Stage:

Require: The input containing all the information of distances
Require: ***L*** {Determine the location}
    for each location l_i
        calculate $P(l_i|x)$
    end
    $\underset{l_i \in x}{\textbf{argmax}}\, P(l_i|x)$

In the testing phase, the corresponding fingerprints are collected and classified based on the feature. The probability of each location is measured and the highest probability is selected for the estimated location which corresponds to the closest entry in the database. This is marked as the location of the tag. Based on Bayes theorem, the location is calculated as

$$P(L_i|x) = \frac{P(x|L_i)P(L_i)}{P(x)} \qquad (7)$$

where $P(L_i)$ is the location probability and $P(x)$ is probability of the observed features. $P(x|L_i)$ can be calculated from the training dataset, and is assumed to follow a Gaussian distribution with variance, σ and mean, m.

4.1 Experiment Setup and Environment

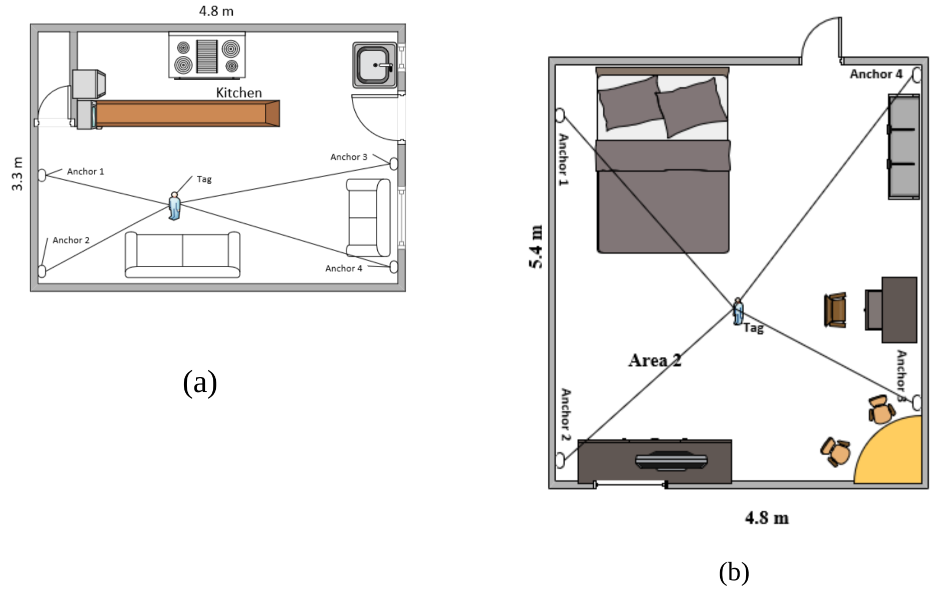

Figure.5: Data collecting and testing enviroments (a) Small-sized & (b) Medium sized room.

Figure 5 shows two different indoor scenarios. As shown in Fig. 5a, the first testing location is a living room and kitchen together. The four anchors are placed in such a way that they have a complete LOS with the tag. The human wears the tag. The size of the room is 3.3 x 4.8 m^2.

The second testing location is another room as shown in Fig. 5b. The size of the room is 5.4 x 4.8 m^2, and the user can move freely within this room. However, the anchors are placed in such a way that they do not have a complete LOS with respect to tag as well as anchors. From the figure, it can be observed that anchor 2, anchor 3 and anchor 4 do not have a direct LOS as it is blocked by the room furniture.

In both the cases the data collection is collected over one complete day. Furthermore, during the process of collecting data the human orientation and stance remained unchanged. However, after the training is carried out, the human can move freely within this room.

4.2 NB and ROC Results

Figure 6 below shows the summary of the result using the NB classifier which is obtained by WEKA machine learning software. From the figure, it can be observed that out of 1144 classified instances, 1037 instances were classified correctly, resulting in an accuracy of 90.6469%. The reason for high accuracy is that the testing is carried out in a small-sized room having a complete LOS environment as mentioned in Fig. 5a. The remaining 107 cannot be correctly classified. As the classification results are compared with the actual locations, the confusion matrix can be developed which will assist us in analyzing the errors made by our NB classifier. From the generated confusion matrix, it can be observed that 185 samples (adding the elements in the third column) can be classified as highly accurate, 938 samples (adding the elements in the second column) are having medium level of accuracy, and 21 (adding the elements in the first column) samples have very low accuracy. Most errors occur when the sample is classified as a medium level instead of having a low level of accuracy.

```
=== Summary ===

Correctly Classified Instances        1037              90.6469 %
Incorrectly Classified Instances       107               9.3531 %
Kappa statistic                          0.637
Mean absolute error                      0.0745
Root mean squared error                  0.2143
Relative absolute error                 53.7501 %
Root relative squared error             81.6851 %
Total Number of Instances             1144

=== Detailed Accuracy By Class ===

                 TP Rate  FP Rate  Precision  Recall   F-Measure  MCC      ROC Area  PRC Area  Class
                 0.615    0.011    0.381      0.615    0.471      0.477    0.990     0.531     Low
                 0.911    0.121    0.983      0.911    0.946      0.657    0.947     0.990     Medium
                 0.899    0.076    0.578      0.899    0.704      0.682    0.962     0.875     High
Weighted Avg.    0.906    0.115    0.934      0.906    0.915      0.657    0.949     0.973

=== Confusion Matrix ===

   a   b   c   <-- classified as
   8   5   0 |   a = Low
  12 922  78 |   b = Medium
   1  11 107 |   c = High
```

Figure 6: Naïve Bayes classifier results for small-sized room

Figure 7 below shows the summary of the result using the NB classifier which is obtained by WEKA machine learning software. From the figure, it can be observed that out of 531 classified instances, 464 instances were classified correctly, resulting in an accuracy of 87.3823%. The reason for low accuracy is that the testing is carried out in a medium-sized room having partial LoS environment as mentioned in Fig. 5b. The remaining 67 cannot be correctly classified. As the classification results are compared with the actual locations, the confusion matrix can be developed which will assist us in analysing the errors made by our NB classifier. From the generated confusion matrix, it can be observed that 18 samples (adding the elements in the third column) can be classified as highly accurate, 432 samples (adding the elements in the second column) are having medium level of accuracy, and 81 (adding the elements in the first column) samples have very low accuracy. Most errors occur when the sample is classified as medium level instead of having a low level of accuracy. Let us know calculate the ROC of these rooms.

```
=== Summary ===

Correctly Classified Instances         464               87.3823 %
Incorrectly Classified Instances        67               12.6177 %
Kappa statistic                          0.6416
Mean absolute error                      0.0881
Root mean squared error                  0.2659
Relative absolute error                 34.3039 %
Root relative squared error             74.3761 %
Total Number of Instances              531

=== Detailed Accuracy By Class ===

                 TP Rate  FP Rate  Precision  Recall   F-Measure  MCC      ROC Area  PRC Area  Class
                 0.602    0.031    0.840      0.602    0.701      0.650    0.872     0.778     Low
                 0.960    0.362    0.891      0.960    0.924      0.661    0.887     0.947     Medium
                 0.647    0.014    0.611      0.647    0.629      0.616    0.931     0.723     High
Weighted Avg.    0.874    0.280    0.871      0.874    0.867      0.657    0.885     0.904

=== Confusion Matrix ===

   a   b   c   <-- classified as
  68  44   1 |   a = Low
  10 385   6 |   b = Medium
   3   3  11 |   c = High
```

Figure 7: Naïve Bayes classifier results for medium-sized room

Finally, Figure 8 shows the ROC curve for a small- and medium-sized room as mentioned in Figure 5. In this figure, true positive rate (TPR) is plotted against the false positive rate (FPR). Figure 8, it can be observed that area under the curve (AUC) for the small-sized room is more than 0.94, which is an indication that the NB classifier for the UWB based IPS performance is very good. The main reason forth is good performance of the NB classifier is the presence of strong LOS and a small area of the room. This curve also indicates that most data can be classified correctly and the distance and stability of UWB evaluation are relatively high. From

Figure 8, it can be observed that area under the curve (AUC) for the medium-sized room is more than 0.88, which is lower than the small-sized room. However, the AUC is still good enough despite the presence of NLOS. In the future, we will design stronger classifier algorithms that can improve the accuracy performance of the UWB system, especially in the NLOS environment.

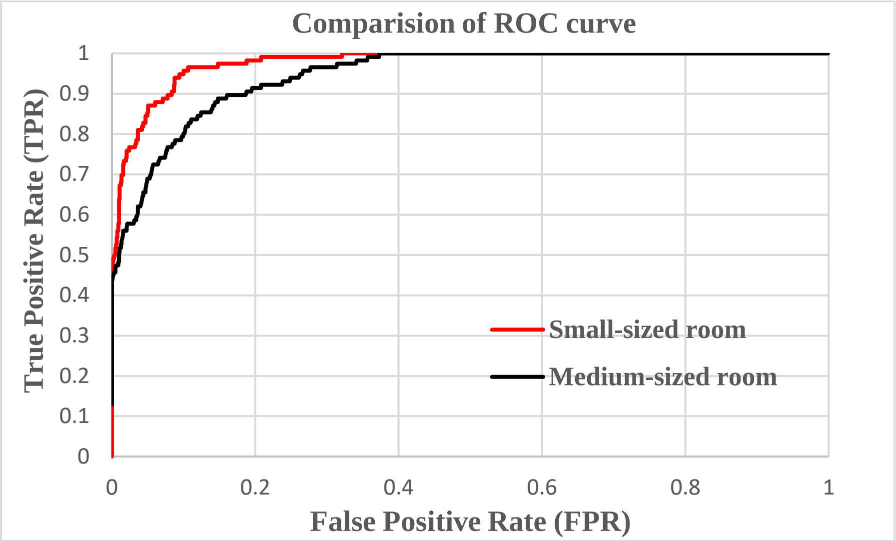

Figure 8: ROC curve of Different Area

5. Conclusion

In this chapter, we have designed a NB classifier for a UWB based localisation system. With the help of NB classifier and RMSE the data is classified into three categories which are high, medium and low accuracy. ROC are plotted to show the effectiveness of the NB classifier. As our developed technique obtains more than 90% classification accuracy, we have tested it into two different environments, which is LOS and partial NLOS conditions. Furthermore, to test the accuracy small- and medium-sized room were used. From our measurements, it is observed that the accuracy of the developed NB classifier is dependent upon the environment. For LOS and NLOS environment, the accuracy is around 97% and 87.38%, respectively. Our future research will concentrate on technique which can further improve the localisation classification and improve the positioning accuracy of the IPS.

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