UTILIZING MACHINE LEARNING ALGORITHMS FOR LOCALIZATION USING RSSI VALUES OF WIRELESS LAN

Chirantan Ganguly[1], Sagnik Nayak[1], S. Irene[2], Anil Kumar Gupta[3], Suresh V.[3], Pradeep Kumar CH[3]
[1]Institute of Radio Physics and Electronics, University of Calcutta, Kolkata, West Bengal India, [2]Center for Development of Advanced Computing (CDAC), Chennai, Tamil Nadu, India, [3]Center for Development of Advanced Computing (CDAC), Pune, Maharashtra, India

NOTE: Corresponding author: Chirantan Ganguly, chirantanganguly01@gmail.com

Abstract *– With the development of new technologies, there has been an upsurge in the demand for precise localization in both outdoor and indoor environments. While a Global Positioning System (GPS) provides sufficient positioning precision in outdoor settings, its accuracy declines in indoor scenarios, necessitating the development of novel positioning approaches that function accurately both indoors and outdoors. The use of various Wireless Local Area Network (WLAN) parameters for localization has been conceptualized. In this study, we attempt to do localization using machine learning methods on WLAN Received Signal Strength Indicator (WLAN RSSI) measurements. We compare the performance of multiple machine learning algorithms on the data set to see which can be used to design efficient future localization systems. The proposed study has achieved second place for the problem statement "ITU-ML5G-PS-016: Location estimation using RSSI of wireless LAN" in AI/ML in 5G Challenge 2021 organized by the International Telecommunication Union.*

Keywords – Fingerprinting, localization, localization algorithms, machine learning, multi-lateration, RSSI, WLAN

1. INTRODUCTION

With the advent of novel technologies such as Augmented Reality (AR), robotics and the Internet of Things (IoT) the demand for precise and reliable location information is becoming increasingly critical. In the current scenario, the Global Positioning System (GPS) is still leading the steam in localization [1]. As we already know GPS technology is based on satellite signals, and it is capable of giving precise location information in outdoor scenarios. However, as the number of satellites visible to the GPS receiver drops and the influence of reflection from walls degrades the signal quality, its accuracy declines in indoor conditions [2]. Mathematical estimates and experimental results show that GPS signals inside buildings are significantly attenuated, reaching levels of 2.9 dB per meter of structure [3, 4]. This large attenuation of GPS signals serves as a barrier for engineers to put it to use indoors. For detecting GPS signals transmitted from indoors, the receivers have to possess the ability to detect signals with power levels of approximately between −150 dBw to −200 dBW. This is especially challenging as the sum of all the unwanted signals (noise) within a measurement system at room temperature is at about −130 dBW level. [5]

As a result, with the increased demand for indoor localization in places like airports, shopping malls, and tunnels, relying solely on GPS would not be sufficient. Therefore, Indoor Positioning Systems (IPS) are being developed to deliver accurate locations in indoor situations using alternative technologies [6].

Various signal parameters of wireless LAN which is widely in use in today’s scenario is being used to develop functioning IPS systems. The use of the Received Signal Strength Indicator (RSSI) of the radio signal received at the Reference Point (RP) from the Wi-Fi Access Points (AP) or Base Station (BS) of cellular systems has gained a lot of traction among the various other parameters used because such systems can be developed without the need for additional hardware components. [7].

The objective of this study is to see how effective ML algorithms are in performing localization using RSSI values observed at the endpoint. We test the performance of various approaches and ML algorithms on a localization data set and compare computational complexity to find the best performing model. The study also explores the theory behind the use of RSSI-based location estimation, the challenges associated with it, and the ways to overcome those challenges.

2. THEORY ABOUT RSSI

The strength of the signal (signal energy) received at the APs for each transmitted information packet can be measured. This received signal energy can be quantized to a form known as the Received Signal Strength Indicator (RSSI). Thus RSSI is actually a measurement of the RF signal power received by radio receivers.

As the received power (P_r) at any radio receiver in an ideal transmission case, where an infinite vacuum exists around the transmitter and reception antenna, the transmitted power can be expressed using a Friis Transmission Equation [8] as:

$$P_r = P_t G_t G_r \left(\frac{c}{4\pi f R}\right)^n \ (W) \tag{1}$$

$$P_r(dBm) = P_t(dBm) + G_t(dB) + G_r(dB) - 10n\log(R) - 10n\log(f) - 32.44 \tag{2}$$

Where P_t indicates the power transmitted by the transmitting antenna, G_t and G_r respectively signify the gain of the transmitting and receiving antenna. R signifies the distance between the transmitter in meters and receiver antennas, and f represents the frequency of the transmitted signal in MHz.

If we consider the transmitter antennas to be of unity gain then the calculation simplifies as

$$G_t(dB) = G_r(dB) = 0\ dB \tag{3}$$

Thus the relation simplifies to

$$P_r(dBm) = P_t(dBm) - P_{Loss}(dBm)$$
$$= P_t(dBm) - 10n\log(R) - 10n\log(f) - 32.44 \tag{4}$$

The power loss in an ideal transmission case therefore, depends solely on the transmission distance as frequency of transmission is kept constant.

$$P_{Loss}(dBm) = 10n\,log(R) + 10n log\,(f) + 32.44 \tag{5}$$

However, this ideal model does not take into account any effect of obstacles and reflection, which is prevalent in indoor scenarios. A model which we would use in indoor sites must consider shadowing, absorption caused by obstacles and interference caused by reflections. Thus, the power loss at a distance d in such scenarios is expressed as follows:

$$P_{Loss}(d) = P_{Loss}(d_0) + 10n\log\left(\frac{d}{d_0}\right) + X_\sigma \tag{6}$$

In Equation (6), $P_{Loss}(d)$ indicates the power loss of the received signal when it is measured at a distance of d (m), while $P_{Loss}(d_0)$ is the path loss of the received signal when the reference distance is d_0 (m); n indicates the path loss exponent / path loss index which depends on the specific environment in which the signal transmission is taking place and signifies how fast the signal attenuates. X_σ measured in dB is a cover factor where the range of standard deviation σ is 5~10 and the mean value is always 0; the larger the σ, the greater the variance and hence the uncertainty of the model.

Thus the resulting expression for RSSI for the receiving nodes / APs is

$$RSSI(d) = P_t - P_{Loss}(d) \tag{7}$$

When d= d_0 (m), if the RSSI = A, then the resultant expression for RSSI with respect to distance can be given by

$$RSSI(d) = A - 10n\log\left(\frac{d}{d_0}\right) - X_\sigma \tag{8}$$

For the convenience of calculation the d_0 value is taken to be 1 m. As already discussed, X_σ has a mean of 0, given that the number of RSSI values are relatively high.Therefore, the RSSI model which can be obtained with averaging of the results from APs will be independent of X_σ (considering a large number of APs).

$$\overline{RSSI(d)} = \bar{A} - 10n\log(d) \tag{9}$$

Where $\bar{A}$ is the average measured RSSI when the AP is 1 meter away from the transmitter point.

From Equation (9) we see that a clear correlation between distance and RSSI values exists. Thus we can measure the undetermined distance of the transmitting point accurately from the RSSI value and the known $\bar{A}$ and n values.

$$d = 10^{(\bar{A}-RSSI)/10n} \tag{10}$$

The value of $\bar{A}$ can be determined during the experimental setup by taking an average of the RSSI values received at each AP when the signal is transmitted from a distance of a meter. The path loss index (n) value is solely influenced by the transmission environment; it can be determined by comparing a large number of experimental measurements made in the environment where the experiment will be conducted.

Table 1 given below indicates some of the different path loss index values in different environments.

Because RSSI (in dBm) values are usually always readily available on most common devices and as it is related to distance, it can be used to determine the distance between mobile devices and APs without requiring any additional hardware. The simplicity in the relationship of RSSI and distance has motivated a significant amount of research to be dedicated towards the development of RSSI-based techniques for indoor localization.

Table 1 – Path loss index (n) of common transmission media

Transmission environment	Path loss index (*n*)
Free space (ideal condition)	2.0
Urban zone	2.7 - 3.5
Suburban zone	3.5 - 5.0
Indoor system [Line of sight (LOS)]	1.7 - 1.8
Indoor system [Non-line of sight]	3.5

3. LOCALIZATION TECHNIQUES USING RSSI VALUES

Several meticulous strategies have been devised to take advantage of the distance-RSSI relationship and reliably estimate location. We hereby discuss a few of the most extensively studied and established localization algorithms developed by researchers.

3.1 Location prediction using multi-lateration (hyperbolic positioning)

As established from Equation (10), the RSSI values can be put to use to estimate the distance between the RP and the AP once we have determined the value of $\bar{A}$ and the path loss index (n) by undertaking extensive experimentation in the environment where localization is to be done.

In a multi-lateration scheme as shown in Fig. 1, upon the calculation of the distance of the RP from each AP (at least 3) at a point of time, hyperbolic positioning can be used to pinpoint the location of the RP.

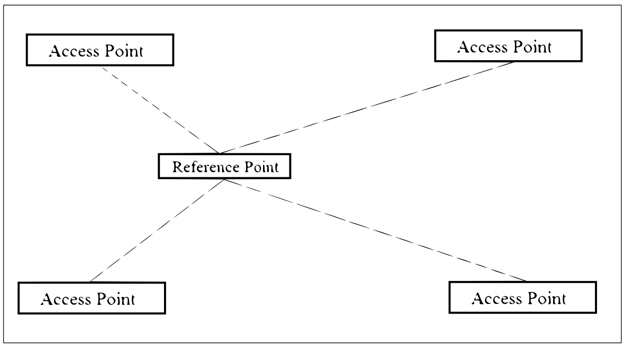

Fig. 1 – Simplified diagram of a localization scheme

For example, if a localization setup has four APs (as in Fig. 1), and they receive a signal at the same time from an RP, we can measure the RSSI at each AP, and from it determine its distance of the RP from each of the four APs. In this kind of setup, we must know the location of the four APs (x_i, y_i). Thus using the relation for Euclidean distance, we can determine the coordinates of the RP by solving the set of simultaneous equations. (11) - (14). This method of locating the RP is diagramatically represented in Fig. 2.

$$\sqrt{(x - x_1)^2 + (y - y_1)^2} = d_1 \tag{11}$$

$$\sqrt{(x - x_2)^2 + (y - y_2)^2} = d_2 \tag{12}$$

$$\sqrt{(x - x_3)^2 + (y - y_3)^2} = d_3 \tag{13}$$

$$\sqrt{(x - x_4)^2 + (y - y_4)^2} = d_4 \tag{14}$$

Even if no two exact values of (x, y) satisfy the set of simultaneous equations, we can determine an area in which the RP is present with certainty, and thereby estimate the location of the RPs with a minimal error, as illustrated by Fig. 3.

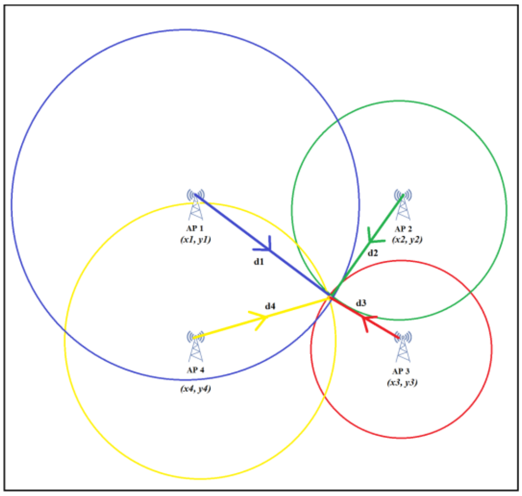

Fig. 2 – Localization using multi-lateration

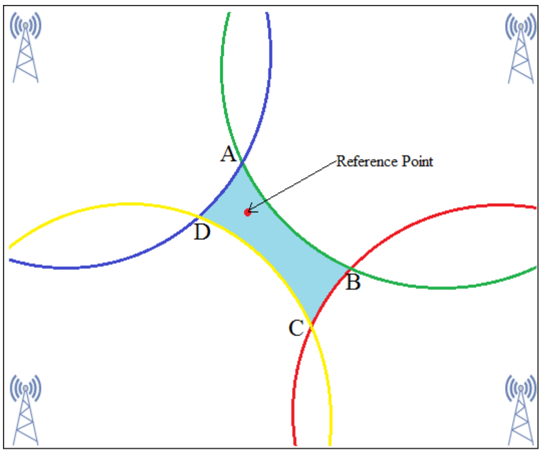

Fig. 3 – Localization using multi-lateration with a certain degree of error

The functioning of the multi-lateration method is however subject to the condition that RSSI values are available at each AP (at least 3) at every instant of time, and is measured with a high level of accuracy [18, 19, 23]. If the data acquired does not fulfill such preconditions, the multi-lateration method would either not be applicable or yield unsatisfactory results. In such a scenario other methods have to be employed for localization.

3.2 Location prediction using fingerprinting technique

Localization using Wi-Fi-based fingerprinting requires a robust RSSI database for a large set of RPs from all accessible AP. This is to be built by rigorous noting of measurements taken in the area where location is to be estimated. An ideal data set of training and testing points for localization using the fingerprinting technique would look like the map shown in Fig. 5.

This robust RSSI data set would thereafter be used for generating a radio signal strength map, as shown in Fig. 4, which is to be used for matching RSSI values to location on the map.

For creating such a fingerprinting model, the training data set must contain a large set of RPs, which are uniformly spread over the area. This will allow us to ensure that the radio map built has a high resolution and small changes in RSSI can also be highlighted and understood for accurate localization [9, 10].

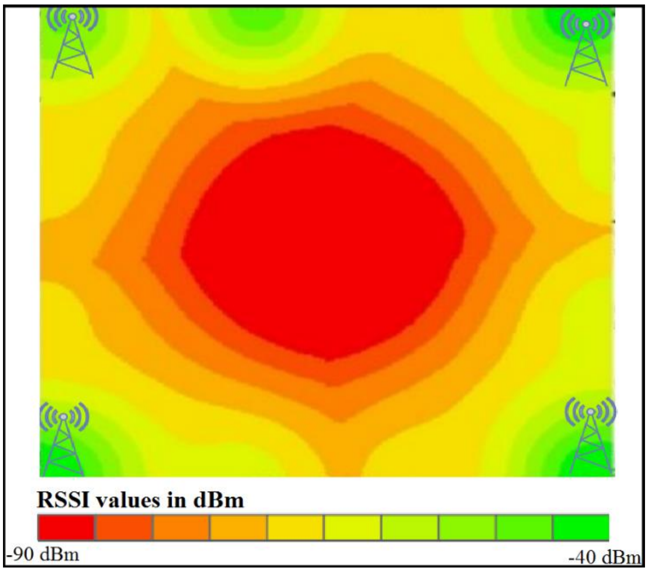

Fig. 4 – Heat map showing RSSI values at various points in the localization area

After the collection of the training database fingerprinting algorithms are used for location estimation. The most commonly used algorithms used in fingerprinting is the nearest neighbor method, whereby points having similar RSSI values are in the training phase can be used to estimate the location of the new RPs.

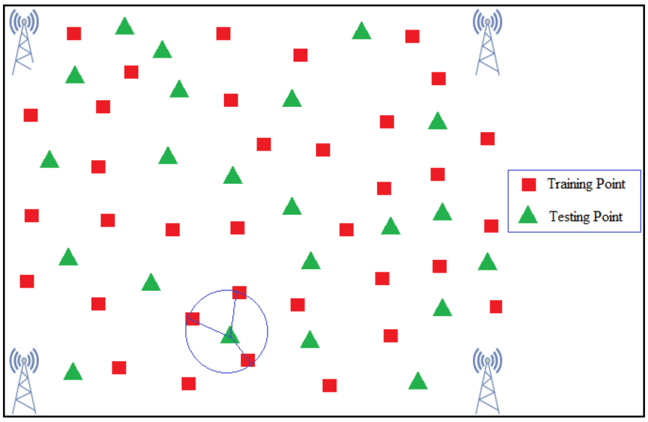

Fig. 5 – Ideal spread of training and testing points for conducting localization using fingerprinting

A significant disadvantage of the fingerprinting approach is that it is highly dependent on the environment, the algorithms need to be recalibrated for even the smallest of changes in the environment, as it can lead to changes in the RSSI values measured at the AP. The fingerprinting algorithm trained for use in a specified environment would not work accurately in a different environment. For using it in a different environment, it needs to be thoroughly trained again with data from a new location. Moreover, the absence of a significant number of RPs would significantly affect the accuracy of the model.

4. NEED FOR FILTERING RSSI VALUES

A clear relationship exists between RSSI and distance which can be exploited to develop localization systems at low cost, as no additional specialized hardware is required for such a technique [11-13]. However, the use of RSSI for localization brings with itself a unique set of challenges, which need to be tackled before the development of such a positioning system.

When signal transmission takes place in a practical environment the effect of multipath fading and multipath interference becomes very prominent. The transmitted electromagnetic waves from the transmitter antenna can either form a line-of-sight connection with a receiver antenna, or the waves can get reflected to the receiver forming a non-line-of-sight connection. The multiple reflections from various objects in the environment makes the waves travel different path lengths. When these different waves interact with each other at the receiver antenna, the strengths of the waves decrease or increase due to interference. Due to this, the RSSI value may show random and rapid changes even though the locations of the transmitting and the receiving antennas have not changed.

Moreover, the received signal power and hence the RSSI value can fluctuate significantly due to obstruction of the path of propagation of the signal by objects (mobile/immobile) [14]. The human body is one of the objects which can lead to a significant amount of Wi-Fi signal shadowing; this is because the human body is made up of 70% water which has a resonance frequency of 2.4 GHz, which is the operational band of Wi-Fi signals [15]. Thus human presence in the localization environment can make the RSSI fluctuate, and therefore reduce the accuracy of the positioning systems.

Fluctuations in the value of RSSI caused by various environmental parameters reduce its correlation with respect to distance, and thereby making RSSI somewhat unreliable to do localization with [16]. Therefore, a significant amount of work done on the development of RSSI-based positioning systems has been efforts towards developing techniques for negating the fluctuations in RSSI [20, 21, 22] and therefore minimizing errors in location estimation.

5. DATA EXPLORATION

5.1 Data sets

We used two data sets for testing the performance of various ML models. The data sets were provided as a part of problem statement 16 of "AI/ML in 5G Challenge" 2021, organized by the International Telecommunication Union (ITU) [17]. The problem statement and the data sets were created and provided to us by RISING, Japan. The two data sets were provided for two rounds of the contest.

The first data set was provided for the competition phase of the AI/ML in 5G Challenge. The data in the first data set was collected from a localization setup utilizing four APs in the outdoors. All the APs were of the same height and were located at four corners of a (50 m x 50 m) localization area. The RPs to be used for training and testing were scattered in the localization area. The RSSI values in dBm were measured from the RP with respect to each AP along with the timestamp and connection channel ID. The location (longitude, latitude) of the APs and the RPs were obtained by GPS, and our objective is to train ML algorithms which can locate the RPs using the RSSI measurements given. The data consisted of only 26 unique RPs for training, and 26 RPs were present for testing. The environmental specifications of each of the APs were also provided. AP1 was located next to a fence, while AP2 was located beside a metal warehouse; AP3 and AP4 were located inside a chaparral. The location of the AP, RPs used for training and testing are shown in Fig. 6.

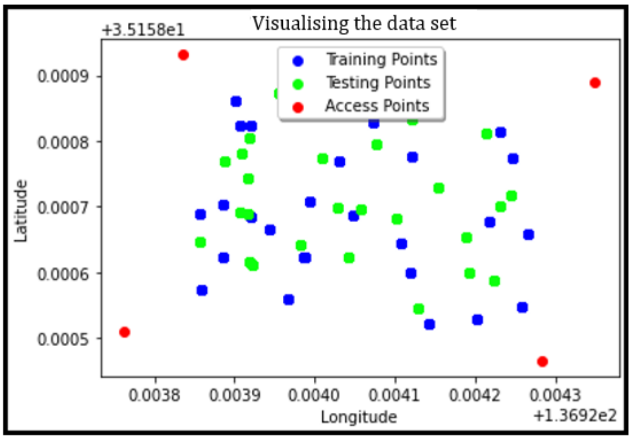

Fig. 6 – AP and RP location in first data set

The second data set had a similar setup as the first one; it had four APs located (35 m x 15 m). This data set however had only 13 RPs for training and 13 RPs for testing. Some of the RPs were also present outside the rectangular area between the four APs, which was not the case in the first data set. The location of the APs and the RPs in the second data set is shown in Fig. 7.

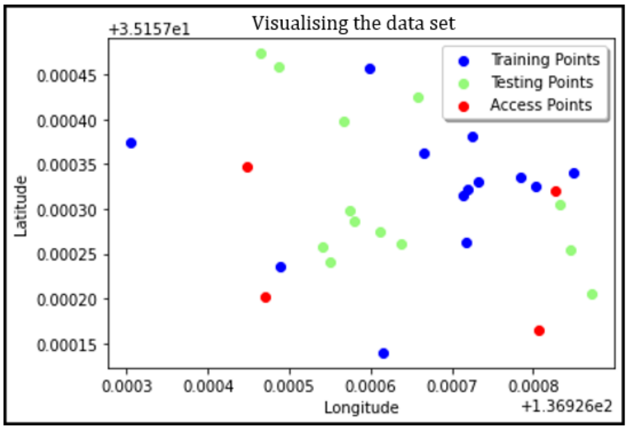

Fig. 7 – AP and RP location in second data set

5.2 Data exploration and preprocessing

Analysis of the data sets was performed, and we observed that the RP received signal from each AP for a period of 100 seconds and the RSSI value of the signal received was measured at the RP at a rate of 100 samples per second. The RSSI measured at the RP with respect to each AP was not synchronized (i.e., RSSI values from different APs were taken at different time instants).

Moreover, in both the data sets, we observed that the RSSI values measured from one point fluctuated and varied randomly in quick succession. This variation could be due to multiple reasons, which are discussed in Section 5. The random variations in RSSI is one of the main challenges for any localization scheme utilizing it as a parameter for localization. These unpredictable variations in RSSI are even more significant when we are using ML models which are required to be trained using this noisy data.

Therefore, data smoothening techniques had to be used to reduce these random variations in RSSI values. For smoothening the sudden variations in RSSI values we used an unweighted moving average technique with an optimal window size of 10. Fig. 8 illustrates the originally provided data with sharp variations and the data after it was smoothened. Apart from smoothening, some outlying values were also removed from both the data sets. Feature selection was done to get rid of the irrelevant features from the provided data set which might negatively impact the performance of the models. We rejected the features which had zero correlation with the final result and therefore were not needed. Finally, after following techniques such as one-hot encoding to convert categorical data into numerical data, for example, the environmental specifications of the AP's location, we restructured the resulting data set in a way that would be suitable for training the ML models.

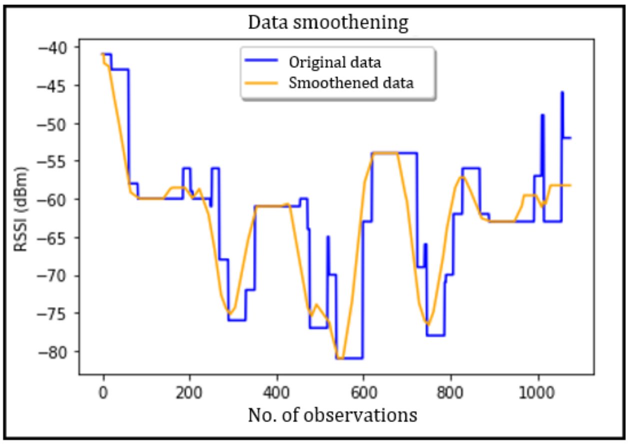

Fig. 8 – Data smoothening using moving averaging

6. PROPOSED SOLUTION

We used multiple machine learning approaches to create the localization algorithm. Both the multi-lateration and the fingerprinting techniques were tested on the provided data sets to see which one would yield more accurate results. For carrying out the multi-lateration technique we used a linear regression model with polynomial features of degree two. We used the linear regression model to first predict the distance of an RP from an AP from the RSSI values. Once the distance of an RP has been measured from a set of three or more APs at one point of time, a multi-lateration technique was used to locate it in the given localization area. The relationship between distance and received power as illustrated by Equation (1) motivated this choice of algorithm. We also used the AdaBoost regressor to enhance the accuracy of the results of distance prediction from RSSI values by using an ensemble of a maximum of 50 estimators.

For conducting localization using a fingerprinting technique (directly predicting the latitude and longitude of the RP without measuring its distance from the AP) we employed a k-nearest neighbor regressor with k=3. For enhancing the performance of the fingerprinting models we again used an ensemble approach using AdaBoost regressor where we used trained two ensemble algorithms – one to directly predict the latitude of the RP and the other to predict the longitude from the features selected.

7. EVALUATION AND DISCUSSION

The accuracy of the estimated distance using the various algorithms as discussed above was quantified by the following evaluation metrics:

(i) Mean distance error of all the distance predictions made (in meters).

$$Mean\ Distance\ Error = \frac{1}{N}\sum_{1}^{N}\left|\left(d_{predicted} - d_{actual}\right)\right| \quad (15)$$

(ii) Maximum distance error among all the distance predictions made (in meters).

$$Max\ Distance\ Error = max\left(\left|d_{predicted} - d_{actual}\right|\right) \quad (16)$$

(iii) Percentage of predicted data with less than 2 meters error.

$$\%\ of\ data\ with < 2m\ error$$

$$= \frac{count\left(\left|d_{predicted} - d_{actual}\right| < 2\right)}{Total\ number\ of\ predictions\ made} \times 100\% \quad (17)$$

Where $d_{predicted}$ is the distance predicted by the developed model, d_{actual} is the actual distance between the RP and AP.The computational complexities of the various models were also measured using their latency. The metrics of the various algorithms were compared with a baseline model which utilized the mathematical equation given in Equation 10 to find the distance and hence the location directly, without utilizing any ML model. The metrics for the various models when applied to both the data sets are shown in Table 2.

From the evaluation metrics it is evident that k-nearest neighbor had the worst performance in both the data sets among the various different models which were experimented with. This poor performance could be attributed to the setup used to form the data sets. For conducting accurate localization using a fingerprinting algorithm a large number of uniformly spread RPs are needed throughout the localization area; however, in the data sets used this was not the case as can be seen from Figures 6 and 7. For improving the performance of k-nearest neighbor the data set used for training the model needs to be much more robust with a greater number of data points; this can be either achieved through a more thorough training phase or by utilizing data augmentation techniques to enhance the data sets.

The AdaBoost fingerprinting algorithm gave consistently the least margin of error in both the data sets with lesser maximum error. Moreover, AdaBoost fingerprinting yielded the highest percentage of data predicted with less than a 2 m error. Although the accuracy of this model is higher, it did have considerably higher latency as compared to algorithms such as linear regression with polynomial features of degree 2 followed by multi-lateration. Since the localization algorithm is needed in scenarios requiring it to locate the point in real time, the high latency would be undesirable. Additionally the linear regression algorithm is much simpler requiring less computing power as compared to the ensemble approach of AdaBoosting.

Table 2 – Evaluation of the performance of different ML algorithms used.

Models	Data set 1			Data set 2			Latency** (in seconds)
	Mean error (in m)	Max error (in m)	%age with <2 m error	Mean error (in m)	Max error (in m)	%age with <2 m error	
Baseline	14.9	50.4	8.85%	12.13	32.46	7.63%	
Linear regression (degree 2)	9.98	27.99	13.23%	10.07	25.79	11.80%	0.08
AdaBoost (Multi-lateration)	10.5	28.99	11.27%	13.78	34.41	7.72%	0.37
k-nearest neighbor (k=3)	20.55	47.28	1.06%	19.23	38	0%	0.017
AdaBoost (Fingerprinting)	15.33	23.29	7.79%	12.33	25.09	23.27%	0.35

** Computed in Intel Xeon CPU operating at 2.2GHz

8. CONCLUSION AND FUTURE DIRECTION

In this study, we explore the problem of localization and the various existing algorithms for such a task. We analyze the performance of ML algorithms to perform localization in two different scenarios. All the different ML algorithms tested were able to outperform the baseline mathematical model. The ML models were able to map the relationship between RSSI values and distance between RP and AP values. From our study we can conclude that even though the fingerprinting model employing AdaBoost regression yielded the best results, it demonstrated considerably higher latency than the other models which were tried out. Polynomial regression therefore can be considered to be as an optimal solution to the given problem yielding decent accuracy with low latency. Models such as k-nearest neighbor can also yield higher accuracy if the testing and data collection phase is conducted in a more robust manner with a higher number of RPs.

The models' performance can be further improved by using filters such as Gaussian and Kalman filters to remove the noise and sudden variation in RSSI data.

Moreover, other parameters of WLAN such as Link Quality Index (LQI), Time of Arrival (ToA) and Angle of Arrival (AoA) may be employed to conduct localization alongside RSSI, as these parameters are not corrupted by the environment as much as RSSI is.

ABBREVIATIONS

i. AoA – Angle of Arrival
ii. AP – Access Point
iii. BS – Base Station
iv. GPS – Global Positioning System
v. IoT – Internet of Things
vi. IPS – Indoor Positioning System
vii. LQI – Link Quality Index
viii. ML – Machine Learning
ix. RF – Radio Frequency
x. RP – Reference Point
xi. RSSI – Received Signal Strength Indicator
xii. ToA – Time of Arrival
xiii. WLAN – Wireless Local Area Network

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AUTHORS

Chirantan Ganguly is currently pursuing his bachelor's degree in electronics and communication engineering from the Institute of Radio Physics and Electronics, University of Calcutta. He has worked as a research associate with Dr. Anamaria Berea, (George Mason University). He is working as a research intern at CDAC, Pune and at Scientific Analysis Group, DRDO. His research interests are artificial intelligence and machine learning application in the development of future communication networks.

Sagnik Nayak is currently a student in the 3rd year of a B.Tech. in electronics and communication engineering from the Institute of Radio Physics and Electronics, University of Calcutta. He served as a Python mentor and an executive member for CodeClub of the University of Calcutta. He has tutored his peers on various machine learning and deep learning concepts and their applications. His research interests include deep learning, the Internet of Things, embedded systems, biomedical electronics, 5G technology, and robotics. He is currently undertaking a research internship under Dr. Anil Kumar Gupta at CDAC, Pune.

S. Irene is Joint Director at the Centre for Development of Advanced Computing (C-DAC), Chennai, India. She has been working in C-DAC since 2006. She completed her M.E in VLSI design from Government College of Technology, Coimbatore and is pursuing a Ph.D at Anna University. She has one patent (applied), four research publications in international and four at national conferences. An idea proposed by her was selected in the top 100 use cases in a 5G hackathon conducted by DoT. Her current research focuses on machine learning, deep learning, computer vision, video analytics and satellite image analysis.

Anil Gupta is a Senior Member, IEEE and Senior Member ACM. He has more than 24 years of industry experience. He received his master's degree from IIT Roorkee, India which is an Institute of National Importance as declared by the Government of India. He also holds a Phd in strategy from west coast University Panama. He has done an MBA(HR) from Calorx Teachers University. Dr. Anil is working with CDAC Pune as an associate director. His research interests are in HPC, SDN, IOT, 5G, data analytics NLP, computer vision, system software blockchains, and cybersecurity. He has more than 70 publications and two book chapters in various national/international conferences and journals. He has filed four patents in India, and multiple patents are in various stages of evaluation. He has guided more than 15 masters' dissertations. He also has guided 25+ B.Tech students for their projects.

Suresh V is working with CDAC Pune in the capacity of Associate Director since November 2012. His current work areas include 5G, IoT, smart cities and allied domains. Prior to CDAC, he was working with C-DOT Bangalore a premier telecom R&D organization of Govt. of India, as a team lead and research engineer for around 12 years. He completed his bachelor's degree in engineering, from the prestigious Government College of Technology (GCT), Coimbatore. Further, he completed his Master of Business Administration from Anna University during his tenure at CDOT. He has more than 20+ years of rich experience in R&D, and software development in the telecom/NMS/IoT/5G domain. He has been involved in projects of national importance, and was associated with telecom and IT product development, application-oriented research and developments. His areas of interest include 5G, NMS, IoT/M2M, intelligent transportation systems and smart cities. Apart from driving development projects, he is also involved in organizing technical and personality development programs. He is part of various national level working groups, forums and other similar initiatives contributing to the technical and standards community.

Pradeep Kumar Ch is working for the Centre for Development of Advanced Computing as Sr.Technical Officer. He received aBTech degree in computer science engineering from Jawaharlal Nehru Technological University and has 10 years of working experience in software design and development. He worked on various projects related to image processing, computer vision, ubiquitous computing, and Internet of Things, artificial intelligence and machine learning. He is a technology enthusiast and competitive programmer. His research interests include information security, machine learning and Internet of Things.