Progress In Electromagnetics Research C, Vol. 158, 253–260, 2025

PIER C

(Received 30 April 2025, Accepted 5 August 2025, Scheduled 17 August 2025)

ML-Based Hybrid Approach for Improved Indoor Source Localization

Soma Simritha Rao, Madhireddy Sumana, Achanta Dattatreya Sarma*, Tunguturi Sridher, and Kuruva Lakshmanna

Department of Electronics and Communication Engineering (ECE), Chaitanya Bharathi Institute of Technology (CBIT) Gandipet, Hyderabad, Telangana 500075, India

ABSTRACT: The field of navigation has been relentlessly evolving to fulfil its long-standing objective of building a highly accurate universal navigation system. However, in highly urban and indoor locations, line-of-sight signals cannot be guaranteed, and conventional terrestrial-based and satellite-based techniques cannot perform optimally. This paper strives to establish navigation via signals of opportunity (NAVSOP) by proposing a Wireless Fidelity (Wi-Fi)-based indoor localization method using Received Signal Strength Indicator (RSSI) technique. This proposed method employs fingerprinting along with the K-Nearest Neighbour (KNN) and again KNN with Inverse Distance Weighting (IDW) approach to offer superior position estimation accuracy. In this paper, we develop a new neighbourhood dataset by expanding target neighbourhood locations by random point generator algorithm, thereby propounding the utility of NAVSOP for indoor environments to enable future navigation applications in real-world civilian and military domains. The results obtained via the novel IDW approach give a reduced uncertainty in position error estimation of 0.68 m as compared to the traditional approaches of fingerprinting with KNN (1.13 m) and trilateration (2.3 m).

1. INTRODUCTION

Over the past couple of decades, there has been a paradigm shift in the field of navigation. While initially, navigation systems primarily aimed to position and guide single standalone systems like a car, the focus has now shifted to achieving navigation awareness of multiple interdependent systems with a high degree of accuracy. To keep up with the rapid advancements in the sphere of communication technology, the need for a robust navigation system that performs consistently well in any given environment, outdoor or indoor, irrespective of terrain or weather conditions is ever-increasing. Previously, a navigation accuracy of 5–10 m seemed to be a luxury before the advent of Global Navigation Satellite System (GNSS) technologies that provide an appreciable location accuracy of 0.3 to 5 m today [1]. However, over time the limitations of GNSS in providing location accuracy and penetrating in indoor setups or regions with non-accommodative terrain such as inside airports, high-rise buildings, narrow alleys, parking spaces, mountainous terrain, and underground locations, became evident. This navigation gap gave rise to the need to look for alternative navigation techniques. One such contemporarily discovered technique is NAVSOP, i.e., navigation via signals of opportunity, which is being actively researched globally to enable foolproof indoor navigation [2–4]. These signals can be combined with GNSS signals to offer unprecedented position accuracy. Examples include Amplitude Modulation (AM), Frequency Modulation (FM), Television (TV), Bluetooth, cellular, Wi-Fi, World-wide Interoperability for Microwave Access (WiMAX), Radio Frequency Identification (RFID) signals, etc. [1, 5, 6].

In recent times, several authors have been working on indoor localization to improve positional accuracy by adopting the latest machine-learning techniques [7]. Without knowing the signal model or propagation characteristics, Shoari and Seyedi [8] tackled the difficulties of localizing an uncooperative target (such as an intruder or jammer) using binary detection data from wireless sensor networks. Using wireless sensor networks (WSNs) and the generalized likelihood ratio test (GLRT), Cheng et al. [9] devised a decentralized detection (DD) of an uncooperative moving object detected in zero-mean unimodal noise. This work's primary unique feature is the suggested Truncated One-Sided Sequential (TOS) test rule, which safely delays decisions under hypothesis H0 while allowing for faster judgments when a target is present (i.e., under hypothesis H1). The issue of target localization in wireless sensor networks over noisy wireless channels to a central fusion center was addressed by Zhang et al. [10]. This work's primary distinctive features are its analysis of low-bit quantized baseband signals (such as 1-bit or few-bit) and power usage in order to maintain localization accuracy while reducing communication overhead.

An enhanced Weighted Path Loss pipeline (WPL) using Geometric Dilution of Precision (GDOP) for beacon selection and Machine Learning (ML) modules for distance estimate is proposed by Santos and Krishsnan [11, 12]. The suggested enhanced WPL pipeline can perform better than its traditional methods and assist in overcoming its inherent limits, according to quantitative and qualitative results from the experimental

* Corresponding author: Achanta Dattatreya Sarma (ad_sarma@yahoo.com).

doi:10.2528/PIERC25043004

Published by THE ELECTROMAGNETIC ACADEMY

data. In industrial plants, Tabella et al. [13] suggested a data fusion method for the detection and localization task using wireless sensor networks. This work's primary unique feature is a feedback system that uses the Bayesian criterion to model defects with the network's highest hierarchical level and send parameters to the lower levels. An improved indoor localization system with ML was proposed by Santos et al. [14]. The suggested approach's primary unique feature is its combination of an ML regression model and conventional Weighted Path Loss Multilateration (WPLM). In RSSI-based localization, the ML component serves as a correction layer to lessen systematic errors.

Xiang et al. [15] and Wang et al. [16] used IDW technique for the localization on a large-capacity, high-resolution location fingerprint database. During the offline phase of indoor spatial location positioning using a fingerprint database, low stability of the sampled measurement data and sparse reference fingerprint data points led to poor spatial location accuracy. To address this issue, Inverse Distance Weighted Interpolation Optimisation Weighted K-nearest neighbour (WKNN) algorithm, based on Grey Prediction Model (Grey Model (GM) (1,1)), was implemented and tested. Subsequently, on the continuation of this work, Zheng et al. [17] proved that there is a necessity in modeling location uncertainty in collected fingerprint data and showed that position accuracy is improved by over 35% through proper modeling of collected data from the field tests. WKNN approach was employed by Peng et al. [18] in which the unknown points' coordinates are calculated using the inverse of the distance as the weight. In their paper, the authors discussed the traditional WKNN based on RSS which resulted in an inaccurate position. To improve the accuracy, they proposed a fusion weighted algorithm. Similarly, Adiyatma et al. [19] have applied IDW method to generate the synthetic database to overcome the limitations of the fingerprinting technique.

A reasonably priced indoor localization system utilizing Received Signal Strength Indicator (RSSI) measurements is presented in our work. The K-Nearest Neighbors (KNN) algorithm, Wi-Fi fingerprinting, and a reinforced IDW technique are all included into the suggested strategy [20, 21]. The final position estimate's accuracy is greatly increased by this interpolation-based reinforcement.

This paper is organized as follows. The procedure to generate the RSSI database and theoretical background on Trilateration, KNN, and IDW approaches are explained in detail in Section 2. Salient features of the indoor environment, along with the operating procedure of the transmitter and receiver modules are described in Section 3. Data collection from each node and the procedure for estimating position errors are presented in Section 4. Comparative analysis of position estimation using Trilateration, KNN, and KNN with IDW techniques is discussed in Section 5. Finally, conclusions are presented in Section 6.

2. THEORETICAL BACKGROUND

The most common method for navigating with wireless access points (WAPs) is to measure the strength of the received signal. The range-based approach, signal fingerprinting, or range-free approach can all be used to determine RSS. In the range-based strategy, localization is performed by determining the distance between the transceiver and WAP, converting RSS to a metric value and using known WAP locations. In signal fingerprinting approach, a data map produced for a set of known sites is used to compare all measured RSS levels. The position of the transceiver is computed using an empirical position estimation algorithm, such as the nearest neighbor algorithm, based on the best match. The range-free method makes use of techniques such as the Gaussian process for target localization [22]. The proposed technique in this paper first uses fingerprinting method combined with KNN technique to calculate the nearest neighbours (NNs) of the target location. The coordinates of these NNs are averaged to find the approximate coordinates of the target node. To verify the accuracy of the estimated target position, a trilateration technique is applied that makes use of radio propagation model to convert RSS Indicator (RSSI) values into distance estimates between receiver modules/anchor nodes and transmitter module/target node. The novel IDW approach for position estimation is employed to further improve positioning accuracy by minimizing the scale of the target location's neighborhood.

2.1. RSSI Database Generation

In the offline stage of the fingerprinting-based approach, the whole area is divided into equally spaced locations called reference points (RPs). The RSSI samples are collected at each location several times. The average of measured RSSI values at each location is calculated and stored in a file along with its corresponding coordinates. For example, if the area of the position estimation system is 100 square meters, the RSSI samples are collected at 100 locations from each receiver module/anchor node [23]. This will produce the RSSI radio map of the prototype environment that will act as the RSSI database which will be further used to train the ML algorithm and later used for the pattern matching of testing (online) and training (offline) locations.

2.2. K-Nearest Neighbour Algorithm

The KNN algorithm is a non-parametric, supervised learning approach used in statistics. The value K denotes the number of the target node's closest neighbours. Artificial Intelligence (AI) and Machine Learning (ML) algorithms are often used to enhance the accuracy of fingerprinting and have had a lot of success in indoor localization applications in recent years [24]. The capacity of AI/ML techniques to make smart and autonomous decisions using observed data without the necessity for precise mathematical formulation is their most distinguishing feature. ML has also proven to be a useful tool for combining multidimensional data gathered from a variety of location sensors, technologies, and methods, and analysing it as a whole. KNN ML algorithm is utilised in this paper to increase the accuracy of classic localization methodologies due to the aforementioned benefits of implementing ML techniques.

The distances between the measurements in the training phase, consisting of RSSI values obtained at evenly spaced

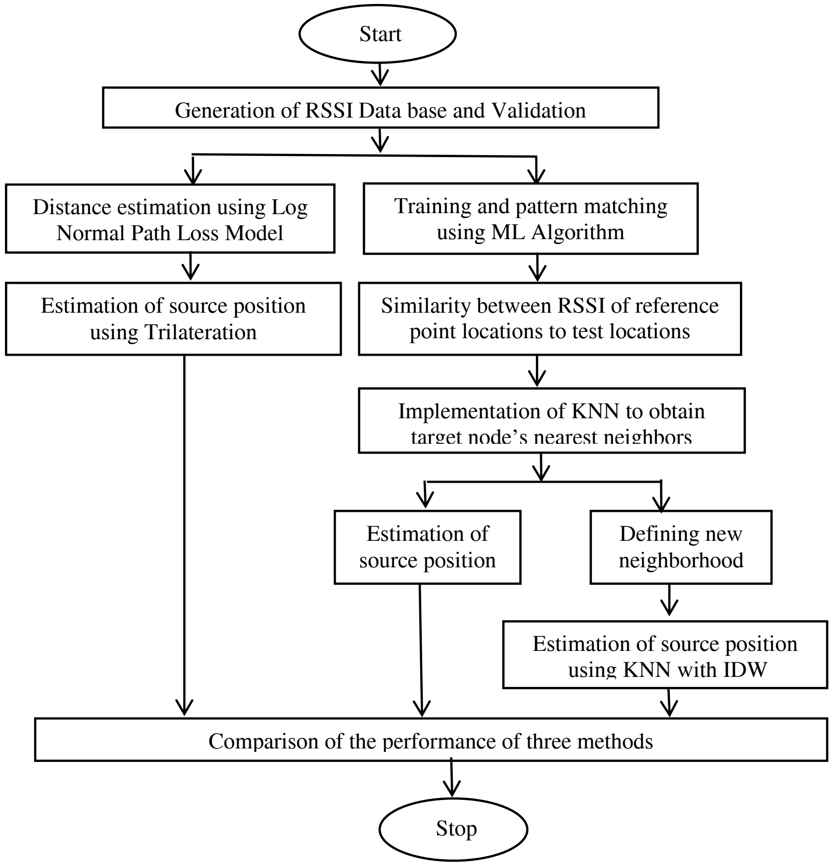

FIGURE 1. Flowchart for important steps in the methodology.

sites, and the measurements of the target now placed at random locations in the testing phase are computed using this approach. The Euclidean distance is the most often used distance measure.

This technique selects K nearest neighbours or reference points (RPs) from the prototype environment's radio map with the shortest distances to the target node. The coordinates of these RPs are averaged to estimate the location of the target node.

2.3. Trilateration Algorithm

The term trilateration refers to a method of estimating the target position using distance measurements from three fixed points. In layman's terms, it is a method for calculating the point of intersection of circles with three fixed locations as their centers. To translate RSSI observations to distance estimations, the conventional radio propagation model or path loss modeling is utilized. The position is determined using the equation of circles once the distance estimates are obtained [25–27].

2.4. Inverse Distance Weighting (IDW) Method

IDW is a particular form of deterministic method for multivariate interpolation that makes use of a predetermined distributed set of points. A weighted average of the values present at the nearby known points is used to determine the values that are allocated to unknown points. It assumes that values nearby have a stronger relationship with their function than those farther away. The inverse of the distance (between the data point and projected location) raised to the power p is used to calculate weights. Thus, as the distance increases, the weights rapidly decrease depending on the value of p. A general form of finding an interpolated value H at a given point based on samples h_i for $i = 1, 2, 3, \dots n$ using IDW is an interpolating function [28]:

$$H_p = \frac{\sum_{i=1}^{n} \left(\frac{h_i}{d_i^p}\right)}{\sum_{i=1}^{n} \left(\frac{1}{d_i^p}\right)} \tag{1}$$

where h is the measured value at known locations, p the power, n the number of points inside the neighborhood, and d the distance from unknown points to known points. When $p = 2$, the method is known as the inverse distance squared weighted interpolation. Once a neighborhood shape has been specified, inverse distance squared weighted interpolation can be performed on the unknown locations in the neighborhood. The salient features of the methodology are presented in Fig. 1.

3. EXPERIMENTAL SETUP

To substantiate the utility of the proposed concept in real-life applications, a smaller experimental prototype environment is set up for testing. For this purpose, the ground floor corridor with dimensions 21.17 m × 3.57 m of the Research and Entrepreneurship Hub in Chaitanya Bharathi Institute of Technology, Gandipet, Hyderabad is chosen as the prototype environment (Fig. 2). Out of this, an area of 60 square meters (20 m

FIGURE 2. Indoor environment for Experimentation in the Research and Entrepreneurship (R&E) Hub.

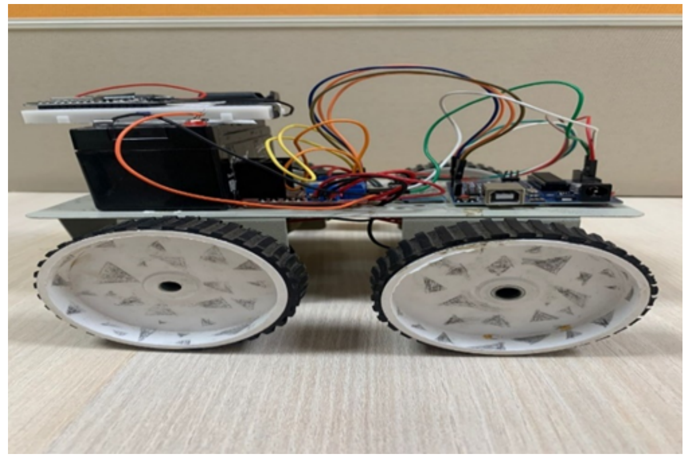

FIGURE 3. Arduino bluetooth controlled robot.

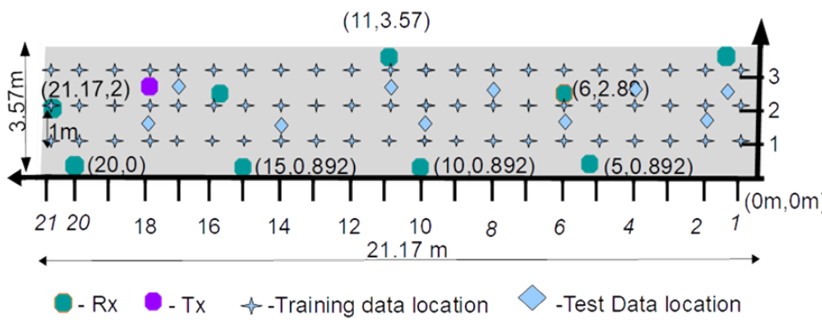

FIGURE 4. Positions of Wi-Fi transceiver modules in the corridor.

$\times$ 3 m) is selected for the experiment. In the offline/training phase of fingerprinting, 60 equally spaced locations separated by a distance of 1 m each in the horizontal and vertical directions are demarcated to act as reference points (RPs) for data collection.

Nine Node Microcontroller Unit (NodeMCU) ESP8266 modules are programmed to act as receivers/anchor nodes that can detect only the RSSI values received from the transmitter/target node via a dedicated, independent channel. One NodeMCU ESP8266 module is programmed to transmit Wi-Fi signals on the dedicated channel, and this module acts as the source/target node to be localized in the experiment. The transmitter module is mounted on a Bluetooth-controlled robot (Fig. 3) that traverses to all 60 locations of the corridor during the offline, training phase. While collecting the data the robot is stationary. The gain of both the transmitter and receiver antennas is 2 dBi.

All the NodeMCU ESP8266 modules used in the experiment have the same specifications, transmit Radio Frequency (RF) signals at a frequency of 2.4 GHz and have a coverage range up to 90–100 m. The NodeMCU transceivers are powered with the help of rechargeable batteries rated at 3.7 V, 2500 mAh. The batteries are soldered to the V_{in} and GND pins of ESP8266 to provide continuous power supply to the modules during the experiment.

These 9 receiver modules/anchor nodes are deployed in the prototype environment at predefined, fixed locations demarcated in the layout diagram of Fig. 4. At each one of the 60 locations where the transmitter is placed, 100 RSSI samples are collected by each receiver. At the end of the offline phase, RSSI values detected at each receiver simultaneously are recorded and stored in real time in the ThingSpeak cloud. This data is exported in the form of a Comma-Separated Values (CSV) file for further processing and analysis. The RSSI values collected at each location are filtered to eliminate data abnormalities. The filtered RSSI samples are averaged for each location. This is followed by the online testing phase in which the mobile transmitter/target node is placed in 10 random locations (Fig. 4), and once again the RSSI values are recorded at each receiver/anchor node module.

4. DATA ACQUISITION AND STATISTICAL ANALYSIS

To achieve the objectives of this paper, the primary step is to establish a channel of communication between the mobile transmitter/target node and fixed receivers/anchor nodes to perform target localization. This is followed by the transfer of recorded RSSI values at receiver modules to a long-term storage platform. The programs required to do so are written in Arduino Integrated Development Environment (IDE) and encoded into the NodeMCU ESP8266 transceiver modules. The transmitter/target node NodeMCU ESP8266 is programmed twice. The first program configures it as a WAP, and the second program integrates the wireless network of this access point with the in-

TABLE 1. Error analysis due to various localization methods.

S. No	Type of error (m)	Trilateration	KNN	KNN with IDW
1.	Mean Error in x direction	0.898	0.44	0.328
2.	Mean Error in y direction	1.983	0.86	0.552
3.	Standard Deviation in x direction	0.666	0.298	0.164
4.	Standard Deviation in y direction	0.694	0.705	0.292
5.	DRMS Error	0.961	0.765	0.335
6.	Overall Euclidean error in distance	2.3	1.13	0.68

ternet. The receiver modules/anchor nodes are all programmed with a common code (since all receivers must be connected to the same transmitter in a localization environment) that connects them to the transmitting node. The histograms of the samples obtained at each location are plotted and superimposed with the standard normal curve to identify the Normal Distribution of data. The standard deviation (S.D.) of the data at each location is calculated to measure how much the RSSI values are spread out from the mean value using the equation,

$$\sigma = \sqrt{\frac{1}{N} \sum\nolimits_{i=1}^{N} (x_i - \mu)^2} \tag{2}$$

where σ is the standard deviation, μ the mean, N the total number of samples ($N = 100$ in this case), x_i the sample value, and $i = 1, 2, 3 \ldots N$. The overall error E in position estimation is calculated by applying the Euclidean distance formula between the actual and estimated coordinates:

$$E = \sqrt{(x - x')^2 + (y - y')^2} \tag{3}$$

where (x', y') and (x, y) are the estimated and real coordinates of the target node with respect to the reference coordinate system (Fig. 4). The mean absolute error for estimated positions is calculated in both x and y directions using:

$$(\Delta x) = \frac{1}{n} \sum\nolimits_{i=1}^{n} |x_i - x'_i| \tag{4}$$

$$(\Delta y) = \frac{1}{n} \sum\nolimits_{i=1}^{n} |y_i - y'_i| \tag{5}$$

and $i = 1, 2, \ldots 10$ for 10 test locations ($n = 10$). The standard deviation (S.D.) in error is obtained in both x and y directions for the position estimations using:

$$\sigma_x = \sqrt{\frac{1}{N} \sum\nolimits_{i=1}^{N} (\Delta x_i - \Delta x)^2} \tag{6}$$

$$\sigma_y = \sqrt{\frac{1}{N} \sum\nolimits_{i=1}^{N} (\Delta y_i - \Delta y)^2} \tag{7}$$

The distance root mean square (DRMS) error can be obtained as:

$$\text{DRMS} = \sqrt{\sigma_x^2 + \sigma_y^2} \tag{8}$$

5. RESULTS AND DISCUSSION

In this section, the position estimation due to experimental data using trilateration, KNN algorithm, and KNN with IDW approach is discussed. The mean error, standard deviation of position estimation error, and DRMS error are calculated and compared to evaluate the performance of these methods.

5.1. Position Estimation Using Trilateration

The Trilateration algorithm computes the target node position by taking the RSSI measurements from three anchor nodes. The distance d between Transmitter (Tx) and Receiver (Rx) is obtained from RSSI received at the anchor node/Rx. The following lognormal path loss model is used to convert RSSI values to distance estimates as it is simple and most suitable for wave propagation and localization concepts [29]

$$PL(\text{dB}) = 10 * n * \log(d/d_0) + PL_0 + \chi_\sigma \tag{9}$$

where $PL = P_t - P_r$ and $PL_0 = P_t - P_{r0}$, and 'd_0' is a reference distance in meters. Here, 'PL_0' is the path loss obtained at the reference distance, 'P_{r0}' the RSSI obtained at reference distance, PL the path loss obtained as a difference of the Transmitter power (P_t) and received RSSI value at a particular distance $d(P_r)$, d the distance between Receiver and Transmitter in meters to be calculated. 'n' is the path loss exponent, and 'χ_σ' is the shadowing parameter and is often considered as a zero-mean Gaussian variable with standard deviation'σ'. The path loss exponent (n) is obtained through the slope value of linear regression. The value generally lies in the range of 1.2–1.8 in indoor, line-of-sight locations. In this experiment environment, we have taken it as 1.2 [27].

Source or target localization is performed using RSSI values recorded at 3 anchor nodes at each of the same 10 test locations, followed by distance estimation and application of trilateration algorithm for position estimation. The obtained results are shown in Table 1. The results show that since the overall Euclidean error, i.e., the distance between the estimated point and actual point is 2.3 m, this position estimation technique is successful in providing only rough estimates with an accuracy up to 2.3 meters along with a DRMS error of 0.961 m.

5.2. Position Estimation Using KNN Algorithm

The ML algorithm of KNN is used for data classification. Since KNN is extremely sensitive to noise, the training dataset fed to the algorithm needs to be standardized, normalized, and refined

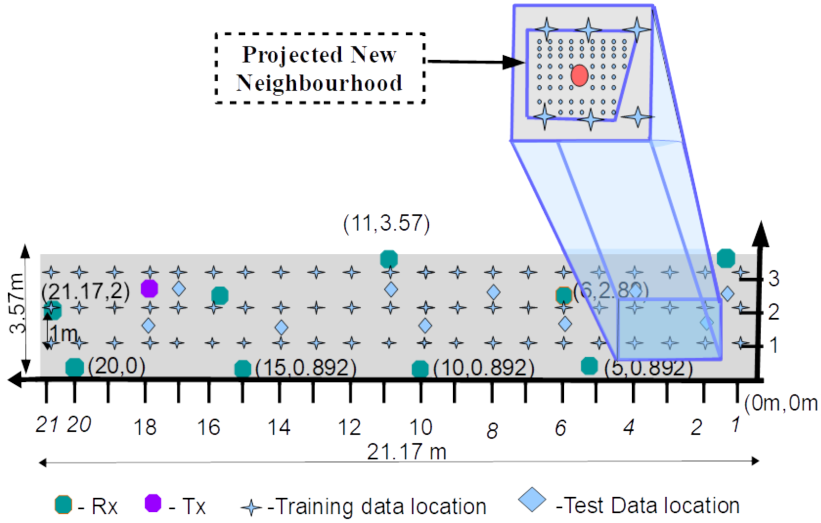

FIGURE 5. Expanded target neighborhood.

before the algorithm is executed. This is done to avoid erroneous predictions. The obtained RSSI database is hence filtered to discard discrepancies by removing the outliers. KNN algorithm is used in the online, testing phase of the fingerprinting technique in which the mobile transmitter/target node is placed in 10 random locations as shown in Fig. 4, and the RSSI values are recorded at each receiver/anchor node module. This testing dataset is pattern-matched with the previously recorded RSSI database to find the coordinates of the NNs or RPs for each of the 10 locations. The NNs are calculated based on the shortest Euclidian distance between the RSSI obtained at each anchor node from the target node in the online phase and the corresponding RSSI database values stored in the cloud during the offline stage [30].

$$d_i = \sqrt{\sum_{j=1}^{n} (RSSI_{ij} - RSSI_j)^2} \tag{10}$$

where d_i shows the adapted Euclidean distance (similarity) between the RSSI value of the i^{th} Reference Point (RP) to the j^{th} point of the test location; $RSSI_j$ represents RSSI values received from the test location; and $RSSI_{ij}$ shows the corresponding RSSI value of the i^{th} RP stored in the database at the j^{th} instance, $i = 1, 2, 3 \ldots N$ and $j = 1, 2, 3 \ldots n$, while n is the number of anchor nodes/receiver modules, and N is the total number of RPs. According to the experiment conducted, $N = 60$ and $n = 9$. The algorithm gave optimum results for $K = 5$.

The implementation of the KNN algorithm ($K = 5$) on the RSSI data obtained from test locations of the target node produces the coordinates of the target node's 5 nearest neighbors as the outcome. The coordinates of all the 60 reference points are fixed according to a predetermined coordinate system and used as a reference for the prototype environment (Fig. 4). The coordinates of these nearest 5 RPs are averaged to estimate the location of the target node. Once the estimated coordinates are obtained, they are compared with the exact coordinates of the test locations. The errors obtained for estimating all the 10 test locations are averaged to give a measure of the efficacy of the algorithm.

The position of the target node is calculated based on pattern matching, i.e., classification of the testing location RSSI measurements with the training RSSI dataset using KNN. Comparative analysis of the algorithm performance for different values of K was done. Based on this, the least error in position estimation was obtained for $K = 5$. Once the 5 nearest neighboring RPs were obtained as a result of KNN implementation, their coordinates were averaged to localize the target node.

The final numerical results obtained for position estimation using fingerprinting with KNN are presented in Table 1. Thus, the results show that this position estimation technique is successful in localizing the target node with an accuracy up to 1.13 m, i.e., an error of 1.13 m between the actual and estimated positions of the target with a DRMS error of 0.765 m which are significantly better than the results of trilateration method.

5.3. Position Estimation Using KNN with IDW Approach

The novel IDW method for position estimation has been employed to help improve positioning accuracy. This is achieved by contracting the scale of the target location's neighborhood as shown in Fig. 5. To do so, the 5 nearest neighbors of the target location obtained during the aforementioned implementation of the KNN algorithm are used for defining the new neighborhood for each of the 10 random target locations (Fig. 5).

Thus, the region enclosed by the 5 nearest neighbors forms the new neighborhood of a target location. This neighborhood consists of 60 new RPs whose coordinates are obtained by interpolating the coordinates of the 5 nearest neighbors that enclose them. A random point generator algorithm is used to generate the new RPs dispersed within each of the 10 new neighborhoods. An RSSI database is generated for each of these new RPs using Eq. (1), which interpolates the existing RSSI values of the 5 nearest neighbors to obtain the RSSI values at the new RPs for each neighborhood. This RSSI database is fed to the KNN algorithm once again as its new training dataset, and the algorithm now chooses K' ($K' = 5$) nearest neighbors of the test/target location from its new neighborhood. Once the new 5 nearest neighboring RPs were obtained as a result of KNN with IDW implementation, their coordinates were averaged to localize the target node.

The numerical results obtained from the position estimation using the KNN with IDW technique are presented in Table 1. The results show that this position estimation technique is successful in localizing the target node with an accuracy up to 0.68 m, i.e., an error of just 0.68 m between the actual and estimated positions of the target with a DRMS error of 0.33 m.

5.4. Comparison and Analysis of Localization Results

Table 1 shows that among the trilateration, KNN, and KNN with IDW approaches, maximum accuracy in position estimation was obtained in the case of KNN with IDW approach which had a Euclidean error of just 0.68 m between the actual and estimated target locations, while the least accuracy was obtained in the traditional trilateration approach that produced an error of 2.3 m. A moderate error of 1.13 m was obtained in the case of fingerprinting with KNN. The mean errors in both x and y directions and DRMS errors are least for KNN with IDW approach, moderate for fingerprinting with KNN, and maximum in the case of trilateration. In the case of KNN with IDW, the standard deviation of error is the lowest too.

It can therefore be deduced that the performance of the KNN with IDW approach is much superior to that of the fingerprinting and trilateration approaches in performing source localization. This can be attributed to the enhancement in accuracy offered by ML techniques adapted by the KNN algorithm along with IDW as opposed to the traditional trilateration technique that is subject to several limitations such as accurate determination of radio propagation constants, multipath, interference, environment dependency, and shadowing measurements, which greatly hinder the accuracy in measurement.

Figure 6 shows the error between actual and estimated coordinates obtained via trilateration, KNN, and IDW methods. We did not use trilateration in the proposed KNN with IDW method. Many state-of-the-art indoor localization approaches require specialized hardware or high computational capacity, but in our experimentation we have used low cost Internet of Things (IoT) modules.

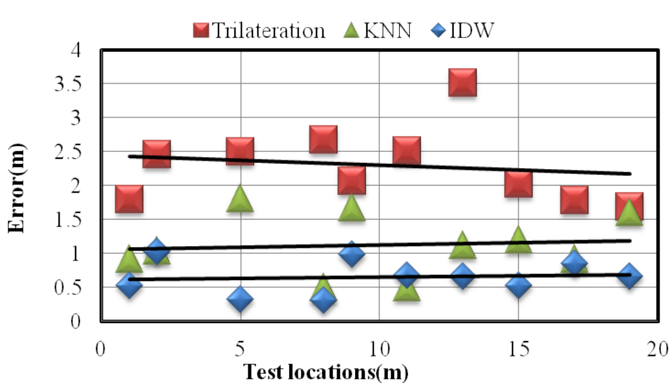

FIGURE 6. Performance comparison of various localization techniques.

6. CONCLUSIONS

This paper has investigated and harnessed the potential of using Signals of Opportunity (SoOP) for the navigation in indoor environments, where high levels of accuracy are required, and GNSS has very limited availability. An integrated approach is undertaken comprising a fingerprinting technique, reinforced by the KNN ML algorithm combined with IDW technique to boost accuracy. The achieved positioning accuracy is 0.68 m for KNN with IDW approach, 1.13 m for fingerprinting with KNN technique, and 2.3 m for trilateration. The performed numerical and graphical analysis concludes that ML with the novel and investigational IDW approach employed in this paper greatly enhances positioning accuracy and can be the future of localization. The errors and challenges encountered during experiment conduction and data analysis as well as the scope for improvements in working methodology to overcome them are studied in detail. The results of this paper are significant in paving the way for the conduction of extensive research in this domain that can be instrumental in making contemporary navigation technology more robust and fool-proof. The present work can be extended by using ML-based algorithms such as Linear Regression, Ridge/Lasso Regression, Support Vector Regression (SVR), Decision Tree Regression, Random Forest Regression, and Gradient Boosting Regression, for improving accuracy. Also for indoor localization position can be augmented with GNSS data to obtain actual geographical coordinates of the position

ACKNOWLEDGEMENT

The work presented in this paper is carried out under the project entitled "A New Model for Short Term Forecasting of Scintillations using Machine Learning Approach and Generation of Regional Scintillation Maps" sponsored by the Department of Science and Technology under the SERB-CRG scheme, vide sanction letter no: CRG/2021/001660, dated February 11, 2022.

REFERENCES

[1] Wang, J., Z. Xiong, Y. Zhao, Y. Ding, Y. Liu, H. Wang, and L. Yan, "Covariance matrix transformation method for absolute/relative measurements fusion of vision/IMU/GNSS integration in parafoil landing," *IEEE Sensors Journal*, Vol. 24, No. 10, 16 673–16 687, 2024.

[2] Raquet, J. F., M. M. Miller, and T. Q. Nguyen, "Issues and approaches for navigation using signals of opportunity," in *Proceedings of the 2007 National Technical Meeting of The Institute of Navigation*, 1073–1080, San Diego, CA, Jan. 2007.

[3] Mitilineos, S., D. M. Kyriazanos, O. E. Segou, J. N. Goufas, and S. Thomopoulos, "Indoor localisation with wireless sensor networks," *Progress In Electromagnetics Research*, Vol. 109, 441–474, 2010.

[4] Yuan, Y., F. Yu, Y. Chen, and N. Zhang, "A method to realize NAVSOP by utilizing GNSS authorized signals," *Journal of Systems Engineering and Electronics*, Vol. 32, No. 5, 1232–1245, 2021.

[5] Leng, M., W. P. Tay, C. M. S. See, S. G. Razul, and M. Z. Win, "Modified CRLB for cooperative geolocation of two devices using signals of opportunity," *IEEE Transactions on Wireless Communications*, Vol. 13, No. 7, 3636–3649, Jul. 2014.

[6] Omer, M., Y. Ran, and G. Y. Tian, "Indoor localization systems for passive UHF RFID tag based on RSSI radio map database," *Progress In Electromagnetics Research M*, Vol. 77, 51–60, 2019.

[7] Zou, H., B. Huang, X. Lu, H. Jiang, and L. Xie, "A robust indoor positioning system based on the procrustes analysis and weighted extreme learning machine," *IEEE Transactions on Wireless Communications*, Vol. 15, No. 2, 1252–1266, 2016.

[8] Shoari, A. and A. Seyedi, "Localization of an uncooperative target with binary observations," in *2010 IEEE 11th International Workshop on Signal Processing Advances in Wireless Communications (SPAWC)*, 1–5, Marrakech, Morocco, 2010.

[9] Cheng, X., D. Ciuonzo, P. S. Rossi, X. Wang, and W. Wang, "Multi-bit & sequential decentralized detection of a noncooperative moving target through a generalized rao test," *IEEE Transactions on Signal and Information Processing over Networks*, Vol. 7, 740–753, 2021.

[10] Zhang, G., W. Yi, M. Matthaiou, and P. K. Varshney, "Direct target localization with low-bit quantization in wireless sensor networks," *IEEE Transactions on Signal Processing*, Vol. 72, 3059–3075, 2024.

[11] Santos, R. X. M. and S. Krishnan, "Augmentation of weighted path loss multilateration via machine learning," *IEEE Sensors Journal*, Vol. 24, No. 2, 2270–2277, 2024.

[12] Santos, R. X. M. and S. Krishnan, "Using machine learning to improve accuracy and robustness of indoor positioning under practical usage scenarios," in *2022 17th International Conference on Control, Automation, Robotics and Vision (ICARCV)*, 978–983, Singapore, 2022.

[13] Tabella, G., D. Ciuonzo, N. Paltrinieri, and P. S. Rossi, "Bayesian fault detection and localization through wireless sensor networks in industrial plants," *IEEE Internet of Things Journal*, Vol. 11, No. 8, 13 231–13 246, Apr. 2024.

[14] Santos, R. X. M., S. Krishnan, and S. M. Sudhakar, "Robust smartphone-based indoor positioning under practical usage environments," in *2022 IEEE 12th International Conference on Indoor Positioning and Indoor Navigation (IPIN)*, 1–8, Beijing, China, 2022.

[15] Xiang, L., Y. Xu, J. Cui, Y. Liu, R. Wang, and G. Li, "GM (1, 1)-based Weighted K-nearest neighbor algorithm for indoor localization," *Remote Sensing*, Vol. 15, No. 15, 3706, 2023.

[16] Wang, P., Z. Feng, Y. Tang, and Y. Zhang, "A fingerprint database reconstruction method based on ordinary Kriging algorithm for indoor localization," in *2019 International Conference on Intelligent Transportation, Big Data & Smart City (ICITBS)*, 224–227, Changsha, China, 2019.

[17] Zheng, Z., Y. Li, Z. Liao, Y. Xue, J. Kuang, Y. Zhuang, and P. Zhang, "The necessity of modeling location uncertainty of fingerprints for ubiquitous positioning," *IEEE Sensors Journal*, Vol. 23, No. 16, 18 413–18 422, Aug. 2023.

[18] Peng, X., R. Chen, K. Yu, F. Ye, and W. Xue, "An improved weighted K-nearest neighbor algorithm for indoor localization," *Electronics*, Vol. 9, No. 12, 2117, 2020.

[19] Adiyatma, F. Y. M., D. J. Suroso, and P. Cherntanomwong, "Fingerprint database enhancement using spatial interpolation for IoT-based indoor localization," in *2022 26th International Computer Science and Engineering Conference (ICSEC)*, 192–197, Sakon Nakhon, Thailand, 2022.

[20] Srinivas, V. S., A. D. Sarma, and H. K. Achanta, "Modeling of ionospheric time delay using anisotropic idw with jackknife technique," *IEEE Transactions on Geoscience and Remote Sensing*, Vol. 54, No. 1, 513–519, 2016.

[21] Prasad, N. and A. D. Sarma, "Ionospheric time delay estimation using IDW grid model for GAGAN," *Journal of Indian Geophysical Union*, Vol. 8, No. 4, 319–327, Oct. 2004.

[22] Kapoor, R., S. Ramasamy, A. Gardi, and R. Sabatini, "UAV navigation using signals of opportunity in urban environments: An overview of existing methods," in *1st International Conference on Energy and Power (ICEP)*, Dec. 2016.

[23] Subhan, F., H. Hasbullah, and K. Ashraf, "Kalman filter-based hybrid indoor position estimation technique in bluetooth networks," *International Journal of Navigation and Observation*, Vol. 2013, No. 1, 570964, 2013.

[24] Nessa, A., B. Adhikari, F. Hussain, and X. N. Fernando, "A survey of machine learning for indoor positioning," *IEEE Access*, Vol. 8, 214 945–214 965, 2020.

[25] Zhu, X. and Y. Feng, "RSSI-based algorithm for indoor localization," *Communications and Network*, Vol. 5, No. 02, 37–42, 2013.

[26] Sridher, T., A. D. Sarma, P. N. Kumar, and K. Lakshmanna, "Distributed RSS-based 2D source localization system in extended indoor environment," *Progress In Electromagnetics Research C*, Vol. 120, 159–177, 2022.

[27] Sridher, T., A. D. Sarma, P. N. Kumar, and K. Lakshmanna, "Results of indoor localization using the optimum pathloss model at 2.4 GHz," in *2020 XXXIIIrd General Assembly and Scientific Symposium of the International Union of Radio Science*, 1–4, Rome, Italy, 2020.

[28] Achilleos, G. A., "The inverse distance weighted interpolation method and error propagation mechanism–creating a DEM from an analogue topographical map," *Journal of Spatial Science*, Vol. 56, No. 2, 283–304, 2011.

[29] Rappaport, T. S., *Wireless Communications: Principles and Practice*, Prentice Hall PTR, New Jersey, 1996.

[30] Gansemer, S., U. Großmann, and S. Hakobyan, "RSSI-based euclidean distance algorithm for indoor positioning adapted for the use in dynamically changing WLAN environments and multi-level buildings," in *2010 International Conference on Indoor Positioning and Indoor Navigation*, 1–6, Zurich, Switzerland, 2010.