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Orientation-aware Indoor Localization Using ML

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Abstract

Indoor positioning systems (IPS), one of the emerging technologies, play an important role in the Internet of Things (IoT) that addresses the challenges of GPS in indoor environments. This technology creates a great impact on real world application. Bluetooth Low Energy (BLE) has emerged as one of the most cost-effective, energy-efficient mechanisms for facilitating indoor localization. A problem with many available BLE fingerprinting techniques is that they do not consider differences in signal characteristics due to the orientation of the device, and limited statistical evidence exists to demonstrate variations in performance. The present study developed a machine learning-based indoor localization framework using BLE 5.1 Received Signal Strength (RSS) and Angle-of-Arrival (AoA) data to evaluate the effect of a device's orientation on decimeter-level localization accuracy. Real-world static datasets were assembled under four orientation conditions: North, South, East, and West. In addition, temporal windowing and median-based fingerprint generation techniques were used to alleviate the impact of signal instability on accuracy. Random Forest (RF), k-Nearest Neighbour (KNN), and Multilayer Perceptron (MLP) were used to generate estimates of 2D positions based on the generated fingerprint. Performance of models was evaluated using distance-based error metrics, percentiles, reliability analysis, and the Wilcoxon signed-rank test for statistical assessment. The results obtained indicate that device orientation is a significant factor affecting localization accuracy, and Random Forest (RF) produces more robust localization accuracy than KNN and MLP across each of the four cardinal orientations. The results also illustrated the need to use orientation-aware modeling techniques to create a reliable BLE-based IPS.

Keywords: Fingerprint Approach, Indoor Positioning System, Median Filtering, Orientation Wise Analysis, Static Scenario.

Introduction

Due to the growing need for location services in many areas, like asset monitoring, smart buildings, and health care, IPS are gaining increasing popularity (1). Even though GPS provides consistent outdoor facility, it does not work well inside buildings due to blocked signals, obstruction caused by the environment, or receivers and satellites not being able to obtain line-of-sight (2). Therefore, alternative techniques have been developed to localize positions within buildings and to enhance signal processing methods (3). BLE provides a feasible solution for IPS because of its cost, energy efficiency, and widespread availability. Nevertheless, many BLE-based systems provide position information based on Received Signal Strength Indicator (RSSI), which is impacted by changes in the environment, as well as by multipath propagation (4). In addition, Bluetooth 5.1 introduced AoA, which gives an estimate of the signal's direction by utilizing antenna arrays, resulting more accurate position-discovery when used with RSSI (5).

Most fingerprinting techniques utilize an offline phase to establish a radio fingerprint, and an online phase to locate a user based on real-time measurements (6). Many machine learning fingerprints have been developed, but many researchers have done little more than focus on algorithm accuracy while primarily ignoring user-oriented factors like device orientation (7, 8). Device orientation can affect RSSI and AoA measurements through the effect of antenna design or body shadowing (9). RSSI-based BLE location studies usually do not include the use of AoA in their research (10). While much evidence exists that the human body can attenuate RF

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signals, orientation is not factored into most of these studies (11). Studies typically report only their mean localization error but do no statistical tests on their data. This study describes an orientation based BLE 5.1 fingerprinting framework that uses both RSSI and AoA measurements and statistical testing.

Related Study

Technologies used in indoor positioning can include RFID, Wi-Fi, BLE, Infrared, 5G Cellular, Ultrasonic, and Ultra-Wideband. Each has its unique benefits and drawbacks; combining multiple technologies sometimes provides better localization results (12). For determined the location of a person or object within an indoor facility in real-time when GPS is not an effective means of locating a subject due to the absence of clear satellite signals (13). For example, a study utilized Bluetooth to measure locations based on RSS values and reported that locations were within 1.2 m to 1.4 m of the true location accuracy after applying all algorithm combinations (14).

BLE technology has gained popularity as an indoor localizing technique. The key focus of the paper was on low-cost BLE-based localization through improved RSSI fingerprinting methods, achieving 96% accuracy using Random Forest techniques and also discusses the issues of multipath propagation and the use of data augmentation to improve accuracy (15). Also, Past studies reviews technologies based on BLE Fingerprinting Indoor Positioning (BLE-FPIP) and provides several options for using fingerprinting techniques (deterministic and probabilistic) (16).

Numerous indoor works currently employ BLE beacons because they are inexpensive, low energy and easy installation (17). BLE localization research comparing BLE localization methodologies found that realistic datasets are essential during testing phase (18). Other research focused on how to estimate distance based on RSSI values and applying techniques such as channel transmission and averaging (19). Furthermore, a hybrid BLE localization solution which applies AoA and RSSI value from multiple BLE anchors (20). Fingerprinting is one of the most accepted methods of indoor localization. The study evaluated the effectiveness of fingerprinting due to its cost and energy efficiency by combining algorithms including Weighted Centroid Localization (WCL) and Power Weighted Centroid Localization (PWCL) (21).

To improve localization accuracy machine learning researchers have utilized regression techniques such as SVR, Boosted Trees, and GPR to enhance the accuracy of IPS (22). The combination of fingerprinting and machine learning creates models that connect RSSI values from the radio map to the actual location within an indoor environment (23). Machine learning algorithms, such as Naive Bayes, SVM, and KNN, have produced high levels of accuracy for IPS over many different spaces. Different types of algorithms machine learning algorithms can also take advantage of Augmented RSSI Data to reduce localization inaccuracies in dynamic situations (24). KNN-based approaches produced accuracy greater than 98% and demonstrated high precision, recall and F1 scores (25).

The significance of device orientation for RSSI measurements in localization cannot be overstated; RMSE decreases from 4.21–5.73 m to 4.04 m when accounted (26), and other research has also indicated that RSSI values change depending on the orientation of the device and should therefore be included in the fingerprint database to enhance positioning accuracy (27). In addition to confirming that random orientations of devices could hinder signal propagation and system performance (28), could be viewed as limited overall; in conclusion, orientation will be a key factor in the design of fingerprint-based models for systems designed to locate devices accurately and will also highlight the need for more accurate fingerprinting models that account for device orientation as applied to BLE versus Wi-Fi fingerprinting techniques for future research into indoor positioning (29, 30). The results of the analysis demonstrated how using statistical tests can improve the reliability of the localization system (31).

Prior research has demonstrated BLE to be a low-cost means of locating users indoors, and also that machine learning-based fingerprinting works effectively. However, there is limited research on RSS, AOAs, and orientation effects with BLE 5.1, and therefore this study will investigate how orientation affects localization performance through statistical analysis.

Methodology

The objective of this research is to quantitatively experiment on how device orientation impacts the accuracy of indoor localization using a fingerprinting system. Machine learning regression is used to model the nonlinear relationship between BLE signal features and two-dimensional spatial locations. The reason for using a quantitative design was to allow for objective algorithm performance comparisons using common error measures and statistical hypothesis testing.

This research uses a publicly available BLE 5.1 dataset of RSSI and AoA measurements that were collected in a controlled indoor environment (32). The use of publicly available data enhances transparency, provides opportunities for replication, and gives an opportunity for external validation of results.

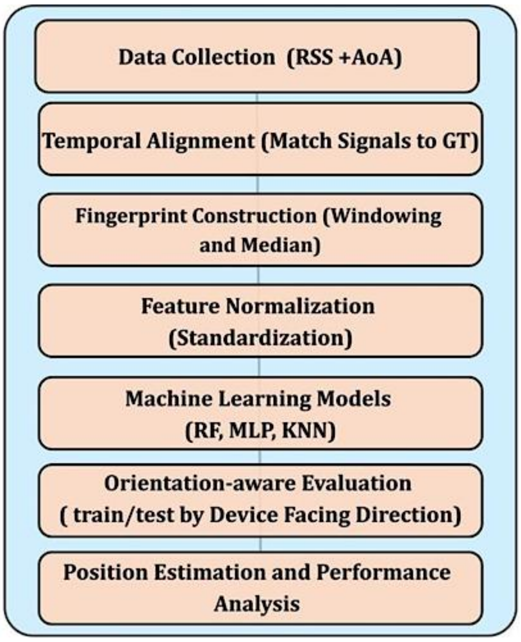

Figure 1: Overall Pipeline of Proposed Methods

Problem Formulation

Indoor Localization can be stated as a supervised regression problem where the goal is to learn the relationship between Wireless Signals and 2D Spatial Coordinates. Based on the collection of BLE Measurements of reference positions is to estimate User Position for a future unseen measurement is shown as Equation [1]:

$$\hat{p} = [\hat{x}, \hat{y}] \qquad [1]$$

At Timestamp t, A tag will read multiple Signal Features from surrounding anchors that include both RSS Measurements and AoA values. The resulting Signal Feature combination will be structured as a signal feature vector as Equation [2]:

$$s(t) = [rss_1(t), rss_2(t), aoa_{az}(t), aoa_{el}] \qquad [2]$$

$$\hat{p} = f(s) \qquad [3]$$

The localization function (shown in Equation [3]) aims to create a map of the relationship between RSS values from the two antennas as well as their corresponding azimuth and elevation angles (i.e., $rss_1(t), rss_2(t), aoa_{az}(t),\ aoa_{el}(t)$) through machine learning tools such as Random Forests, Multi-Layered Perceptron, and k-Near Neighbour regressors. This approach captures more complex non-linear relationships between the characteristics of a signal and its exact position in a building, affected by multipath propagation, shadowing, and fading signals in indoor environments, which are challenging to model analytically.

Dataset Description

The dataset used for this study is the BLE 5.1 indoor localization dataset, publicly available (32). The dataset contains four scenarios; here, static scenario data is used where an individual is stationary for one minute at each of 36 reference locations. These 36 reference locations are approximately 120 cm apart, with the RSS and AOA measurements collected by four anchors. In addition to stationary testing, the measurements will be repeated for each cardinal direction (North, South, East, West) of the subject to investigate the effect of human body orientation on the signals (33). In north orientation collected values is 349853 data with time duration 40.09 min., west orientation collected values is 339568 data with time duration 38.89 min., east orientation collected values is 338235 data with time duration 38.85 min., and south orientation collected values is 332290 data with time duration 37.85 min. This dataset is freely available in web for developed more application in this area. The experimental design provides control for the evaluation of orientation-aware fingerprints and the performance of machine learning-based techniques for indoor localization. Orientation data is combined with ground truth data then the data was divided into 80 and 20 % for training and testing purpose. Two separate folder one for actual beacon data parameters are timestamp, tagid, rss1 value, aoa_az(azimuth) value, aoa_el (elevation) value, rss2 value, anchor_id (6501, 6502, 6503, 6504), and another one is ground truth folder parameters are timestamp, x coordinates and y coordinates.

Methodology Pipeline

The BLE 5.1 indoor positioning pipeline begins with the collection of RSS and AOA measurements from multiple anchors using a tag that an individual wears and mentioned in Figure 1. Ground-truth coordinates are also time synchronized with the signal timestamps to ensure accurate labelling. The stable fingerprints are constructed from the window median features using a windowed method and normalized so that all signals have a uniform scale. Regression models using machine learning algorithms are trained to learn the mapping of signal features to spatial coordinates. Finally, evaluation using orientations and error analysis is completed to determine accuracy of localization.

Temporal Alignment with Ground Truth

In order to provide accurate ground truth location information, precise temporal alignment must take place between signal measurements (beacons) and locations throughout time. For example, at the time of beacon signal measurement (t), the corresponding location can be determined by matching the measured time interval with the corresponding ground truth location record of (x, y) as the location between t_{start} and t_{end} where the ground truth records for location exist. Thus, if as Equation [4]:

$$t_{start} \le t \le t_{end} \qquad [4]$$

Where, t: is a timestamp of beacon measurement.

t_{start} and t_{end}: Start and End timestamp of ground truth collection (x, y): Ground truth location.

Assigning the correct spatial label to an observable signal feature led to reliable supervised learning, reduction of labelling noise and the fingerprint model training. Then, the fingerprint construction can depend on a labelled aligned data set.

Fingerprint Construction and Temporal Windowing

Raw data of RSS and AoA measurements are vulnerable to all of the following short-term fluctuations, Multipath Interference, the Human Body Effect (shadowing the RF signal due to the human body), and changing the orientation of the device. By segmenting fixed lengths of time into segments (windows) to average the value of features over a longer period creates features that will have less variability. A fixed length of time is defined as the amount of time for the window T_w for each reference location (x, y).

Let W_k a set of measurements will be retained for each k^{th} time window represented as Equation [5]:

$$W_k = \{s(t) \mid t_k \le t < t_k + T_w\} \qquad [5]$$

Within a window, the median is calculated for each feature creating a fingerprint shown below as Equation [6]:

$$f_k = [\mathrm{median}(rss_1)\ \mathrm{median}(rss_2)\ \mathrm{median}(aoa_{az})\ \mathrm{median}(aoa_{el})\ ] \qquad [6]$$

The use of the median for calculating the values of a fingerprint provides robustness against Outliers, Signal outliers due to sudden changes in signal, and Noise from types of signals that are not Gaussian.
Each fingerprint will have an associated spatial coordinate mentioned below as Equation [7]:

$$p_k = [x, y] \qquad [7]$$

A complete fingerprint database can be described below as Equation [8],

$$d = \sum_{k=1}^{N} \{(f_k, p_k)\} \qquad [8]$$

Where, N is the number of fingerprints.

The fingerprinting strategy converts the continuous noisy measurement of signals received into stable signal representations at particular locations.
Because the scale of features significantly impacts the outcome of Machine Learning models; thus, it is necessary to normalize all of the features due to the differences in numerical ranges.

To standardize the feature dimensions mathematical formulation is mentioned as below as Equation [9]:

$$\tilde{f}_{k,i} = \frac{f_{k,i} - \mu_i}{\sigma_i} \qquad [9]$$

Where, μ_i= Mean for Feature *i* for the Training Set
σ_i= Standard Deviation for Feature *i* for the Training Set

The standardization of the features provides several benefits like Increased Speed of Model Convergence, Increased Numerical Stability, and Increased Balance of Contribution of each Feature. Both the Training and Test datasets will have the same means and standard deviations, thereby ensuring consistency.

Regression Estimation of User Position

Three different Regression models will be used to estimate the User's location they are RF Regression, MLP Regression, and KNN Regression. These 3 models utilize a different strategy for learning the function $f(s)$.

Random Forest Regression

RF Regression is a machine learning technique based on an ensemble of Mdecision trees. Every tree is trained on a subset of the data sampled at random and a set of features sampled at random. The estimated location of the user (the output of the trees) from each tree (m) will be independent represented as below Equation [10]:

$$\hat{p}^{(m)} = \left[\hat{x}^{(m)}, \hat{y}^{(m)}\right] \qquad [10]$$

Then, the Location estimate is calculated as an average of the outputs from all of the trees as Equation [11]:

$$\hat{p} = \frac{1}{M} \sum_{m=1}^{M} \hat{p}^{(m)} \qquad [11]$$

RF or Fingerprint-Based Localization provides some advantages such as: it is resistant to noise; it is capable of Modelling complex non-linear relationships between the variables; it reduces overfitting through ensemble averaging; and it is well suited for use on small-to-medium size datasets.

Multilayer Perceptron

A feedforward neural network that employs multiple hidden layers for the purpose of learning non-linear mappings is referred to as a MLP.
For the $l$hidden layer, taking an input feature vector $\tilde{f}$, the output of that layer is defined as below Equation [12]:

$$h^{(l)} = \emptyset\left(W^{(l)} h^{(l-1)} + b^{(l)}\right) \qquad [12]$$

Where,
$W^{(l)}$ denotes the weight matrix for the l^{th} layer
$b^{(l)}$ denotes the bias vector for the l^{th} layer
$\phi(\cdot)$ denotes the ReLU activation function
The output layer generates as Equation [13]:

$$\hat{p} = W^{(l)} h^{(l-1)} + b^{(l)} \qquad [13]$$

The MLP is optimized via minimization of the Mean Squared Error (MSE) represented as below as Equation [14]:

$$L_{MSE} = \frac{1}{N}\sum_{k=1}^{N} \|p_k - \hat{p}_k\|^2 \qquad [14]$$

Advantages are the following MLP has strong capacity for non-linear modelling, MLP can learn complex signal patterns, MLP can generalize across different types of environments, and MLP will be a good choice for AoA based localization solutions.

K-Nearest Neighbours Regression

KNN Regression estimates the location of the target via finding the fingerprints stored in the training database $\tilde{f}$ with the smallest Euclidean distances from the test fingerprint $\tilde{f}_i$ via an approach similar to identifying a pattern as below Equation [15]:

$$d_i = \|\tilde{f} - \tilde{f}_i\| \qquad [15]$$

The predicted location of the target given $\tilde{f}$ as the test fingerprint can be calculated as Equation [16]:

$$\hat{p} = \frac{\sum_{i=1}^{k} w_i p_i}{\sum_{i=1}^{k} w_i}, \; w_i = \frac{1}{d_i} \qquad [16]$$

This method provides a method to locate a target using the feature database in a database without the need for model training. Advantages are as follows: KNN is easy to implement, KNN is intuitive to understand, and KNN is likely most effective with a dense fingerprint database.

Localization Error Metrics

Localization accuracy is measured by calculating the Euclidean distance between the estimated and true positions. A test sample, k has its localization error defined as Equation [17]:

$$e_k = \sqrt{(x_k - \hat{x}_k)^2 + (y_k + \hat{y}_k)^2} \qquad [17]$$

Localization performance was evaluated using these metrics:
a) Mean Absolute Error (MAE)
b) Median Error
c) 50th Percentile Error Distance and 75th Percentile Distance

Using percentile analysis allowed for robustness of localization against extreme (non-Normal) localization errors. Therefore, the evaluation of localization performance includes a probabilistic interpretation instead of just relying on a mean-based measure.

Orientation-Aware Evaluation

Four different orientations of the device were used to evaluate localization accuracy independently to assess how orientation impacts performance. The study assesses how much performance can vary from orientation-to-orientation through separate analysis of each orientation and, therefore, can be quantified to understand whether or not there is an overall performance advantage or disadvantage due to orientation. Device orientation has implications on the RSS and AoA characteristics.

To account for this in the dataset, we have divided it according to the device orientation. Let D(o) be the fingerprint database for as Equation [18],

$$o \in \{\text{north, south, east, west}\} \qquad [18]$$

We have trained and evaluated independent models for each device orientation.

Using this orientation-aware model comparison allows us to make fair comparisons in localization performance across different device orientations. The mathematical formulation is modelled as Equation [19]:

$$\hat{p}^{(o)} = f^{(o)}(f) \qquad [19]$$

Statistical Significance Analysis

The Wilcoxon Signed-Rank Test was used to test the statistical significance of performance differences between the models based on the results of the localization error measurement as it does not meet the requirements for normality. Any observed significant difference in localization performance for three models will be determined to be statistically significant if $p < 0.05$.

All data preprocessing, model development and statistical analyses were performed in the Python programming language in the Google Colab environment (CPU Processor). Google Colab was chosen because of its cloud-based computational infrastructure, reproducibility, and compatibility with scientific computing libraries. The following python libraries are used for implementation purpose NumPy, Pandas, Scikit-learn, SciPy, Matplotlib and Seaborn. The use of open-source Python libraries is used to enhance the reproducibility and transparency of the proposed framework. Additionally, the availability of a publicly available dataset and the implementation of a standardized implementation pipeline allow independent validation and replication of the results. Scripts from implementing the models are available for reasonable requests.

Results

In this section, experimental findings of the proposed BLE 5.1 fingerprinting-based solution are discussed, and three different regression methods RF, MLP, and KNN across four different orientations (North, South, East, and West) are evaluated using standard metrics. Additionally, an orientation-wise analysis is performed to evaluate how the orientation of the device impacts the accuracy of the localization.

Overall Model Performance Comparison

The mean comparison of models is presented in Figure 2 displaying average localization error. As shown RF has an average localization error (mean error) of 1.49m. KNN's mean localization error is higher (1.57 m), while MLP mean localization error is almost double that (2.74 m). From this RF model performed better than the other two models, where it has the lowest average error, indicating that the RF model is more effective when it comes to being able to estimate the nonlinear relationship between the signal properties from the RSS/AoA to the spatial coordinates than the k-NN and MLP.

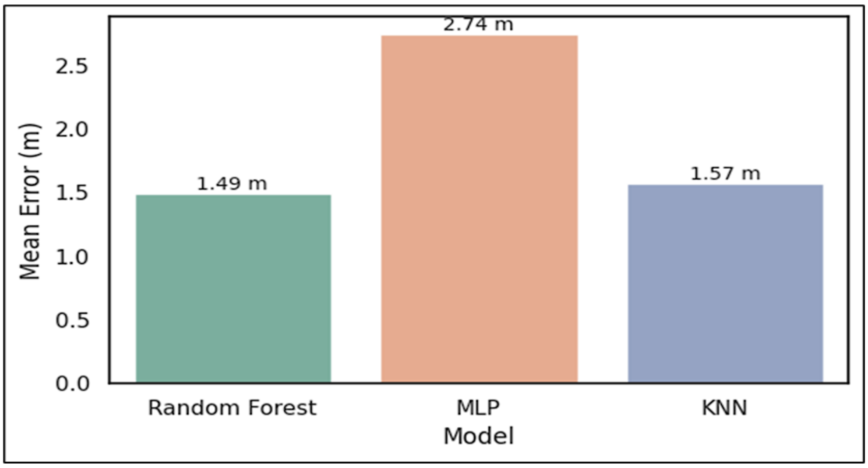

Figure 2: Model-wise Mean Localization Error

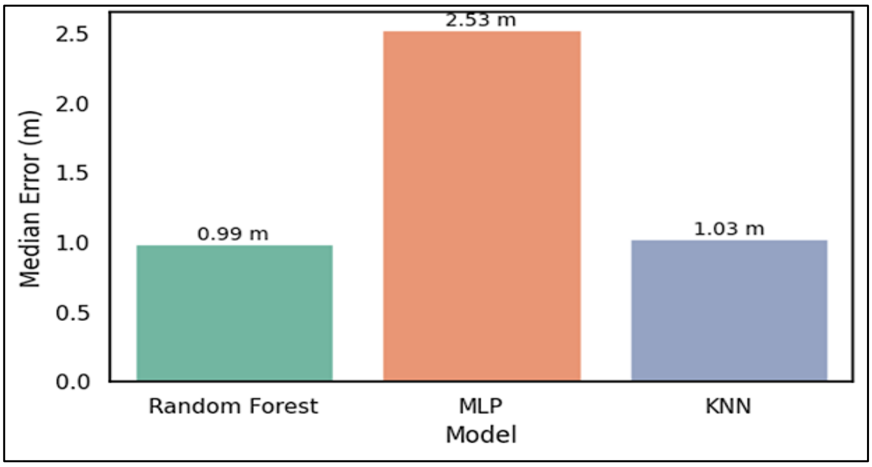

Figure 3: Model-wise Median Localization Error

Since, outlier can adversely affect localization accuracy; the median localization error is represented in Figure 3 to provide a robust performance measure. Illustrate, RF has the lowest median localization error of 0.99 m, while KNN has almost the same value as RF but is only 4cm larger (1.03 m) and MLP has an almost double the median value (2.50 m). The results from the experiment with respect to the RF model once again show that it has the lowest median error across the entire test set, and the difference between the median and average errors is small, indicating that the RF has produced a stable distribution of errors and had fewer outliers. Therefore, these results suggest that using an RF model provides better prediction performance or generalization of the orientation aware BLE fingerprint-based localization problem when compared to k-NN or MLP based predictions.

Orientation performance analysis

An important goal of the present study is to analyse how multiple device orientations have an effect on the accuracy of fingerprint-based positioning inside a building. The study determined device orientation by evaluating localization errors for four controlled orientations (East, West, South, North) across devices. Figure 4 illustrates where MLP model have highest error rate among all orientations and KNN also slightly high error when compare to RF.

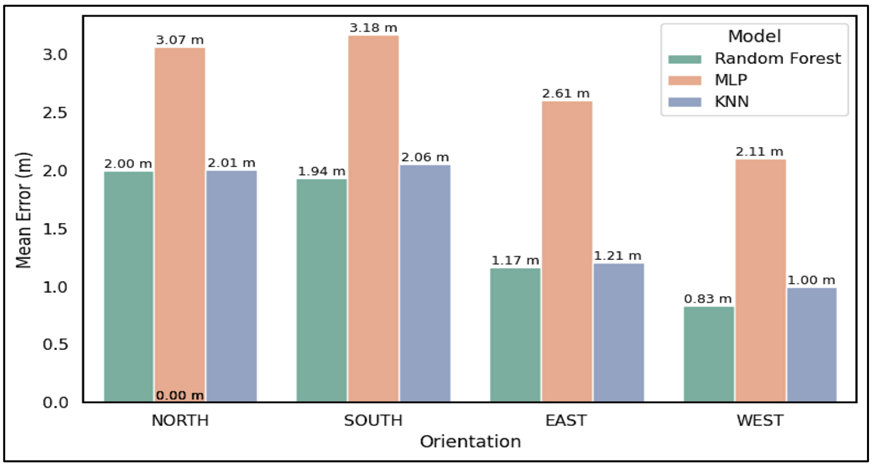

Figure 4: Orientation-wise Mean Localization Error

The best performance across the RF approaches was in the East and West orientations, where the average localization error was less than 1.2 m, and in the West orientation, the average localization error was less than 1.0 m for the RF approach. The average RSS and AoA localization error for the North and South orientations was significantly higher than the other two orientations, with average RSS and AoA localization errors ranging from 1.9 m to 2.1 m. This represent that more distortion due to occlusion and multipath interference occurs in the vertical direction compared to the horizontal direction. The present study confirms that localization error is not invariant across these four orientations, with significant performance variation between orientations. This supports the importance of using orientation-aware approach techniques in the deployment of indoor positioning systems in real-world applications.

A percentile analysis of localization accuracy has revealed an orientation dependency across models and represented in Table 1. In this regard, the West orientation is characterized by the lowest median error and upper percentile error across model types, suggesting that localization performance in this orientation is the most stable and reliable. Conversely, North and South exhibit much greater P75-P95 values than West, indicating that despite geographic proximity, their localization performance will produce greater variance and therefore less reliability. Additionally, it is interesting to note that for the RF, the East direction exhibited significantly lower mean and percentile error values than any other orientation, implying that there is favourable signal propagation characteristics associated with this orientation. When examining all four orientations, RF consistently produced lower median and acceptable percentile errors than MLP and KNN; thus, RF has demonstrated robustness to orientation-related signal distortion in comparison with MLP. In fact, the higher P90 and P95 values associated with MLP in the South orientation indicate substantially worse worst-case performance, reflecting the significant role of device orientation on localization accuracy and reliability within the fingerprinting localization framework.

Table 1: Orientation-wise Percentile Error Rate Comparison in Meter

Mean	Median	P25%	P50%	P75%	P90%	P95%	Orientation	Model
2.00	1.46	0.70	1.46	2.79	4.58	5.65	North	RF
3.08	3.20	1.95	3.20	4.07	5.06	5.37	North	MLP
1.99	1.46	0.61	1.45	2.97	4.74	5.48	North	KNN
1.93	1.28	0.53	1.28	3.28	4.55	5.84	South	RF
3.16	2.79	1.88	2.79	4.79	5.70	6.17	South	MLP
2.08	1.44	0.67	1.44	3.60	4.56	5.62	South	KNN
1.16	0.81	0.31	0.81	1.46	2.68	3.96	East	RF
2.57	2.55	1.60	2.55	3.32	4.01	4.59	East	MLP
1.33	0.96	0.24	0.96	2.01	2.8	4.38	East	KNN
0.83	0.54	0.19	0.54	1.18	2.24	2.71	West	RF
2.16	1.89	1.43	1.89	2.61	3.85	4.36	West	MLP
0.98	0.72	0.24	0.72	1.44	2.39	3.24	West	KNN

Error Distribution Analysis

Cumulative Distribution Function (CDF) curves Figure 5 shows that RF has a smaller error distribution compared to MLP and KNN, suggesting that RF has greater stability and less variance across spatial locations. RF provides a higher cumulative probability for error less than 2 meters than MLP and KNN does, resulting in greater localization accuracy. 80% of the errors produced by RF and KNN are less than 3 meters, while the same is not true for MLP which has a higher error threshold to produce the same level of confidence in localization accuracy. Therefore, the reliability and consistency of positioning performance for RF will be superior to MLP and KNN.

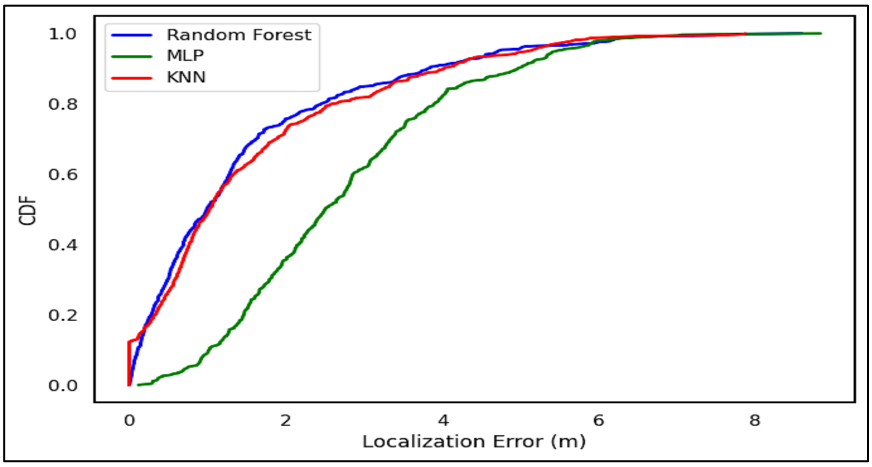

Figure 5: CDF of Localization Error

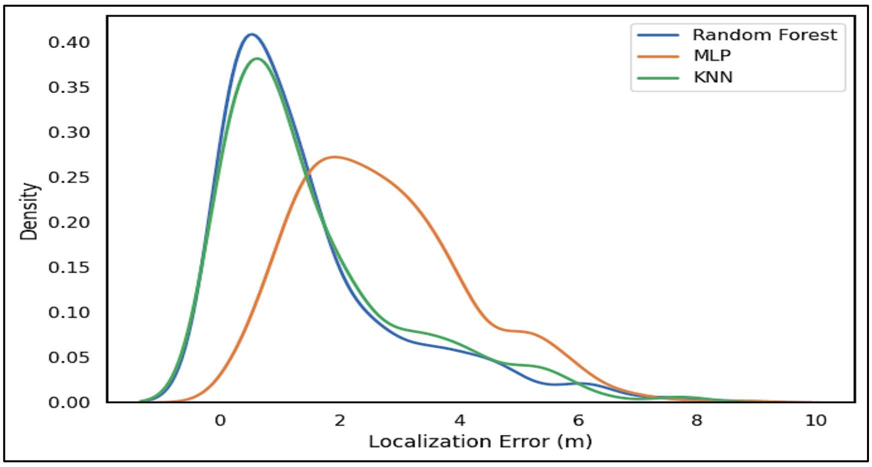

Figure 6: Localization Error Density Comparison graph

In the Error Density plot Figure 6, it can be seen that both RF and KNN have high-density peaks at the lowest error rates around 1 meter; but compare to KNN, RF have some extra peak thus, it provides more stable and consistent localized accuracy. The MLP has a considerably greater range in the distribution of error and has shifted almost entirely to the high end of the distribution, indicating low stability. So, the RF have a high reliable and stability in all condition.

Statistical Testing

The differences in performance observed can be confirmed through statistical analysis in Table 2. All p-values were below the threshold of 0.05 which indicates that the difference in performance between the models is of statistical significance.

The results shown in Table 2 indicate that RF outperformed both MLP and k-NN at $p < 0.05$, suggesting that the superiority of RF is not simply due to chance. Wilcoxon was used as a non-parametric test due to the non-normal distribution of localization errors.

Spatial Error Distribution

To further investigate the behaviour of spatial prediction, both heatmaps and scatter plots were used. The heatmap comparison shown in Figure 7(A-C) shows that RF has lower error values than both MLP and KNN across most of the reference points. The areas surrounding the 'environment' is where RF yields the highest localization errors, due to a reduction in signal coverage from anchors located in those areas.

Table 2: Wilcoxon Signed-Rank Tests (p-values)

ML Models	p-values
RF vs MLP	1.4068334580789612e-52
RF vs KNN	0.022292660797389
MLP vs KNN	7.147600426262583e-46

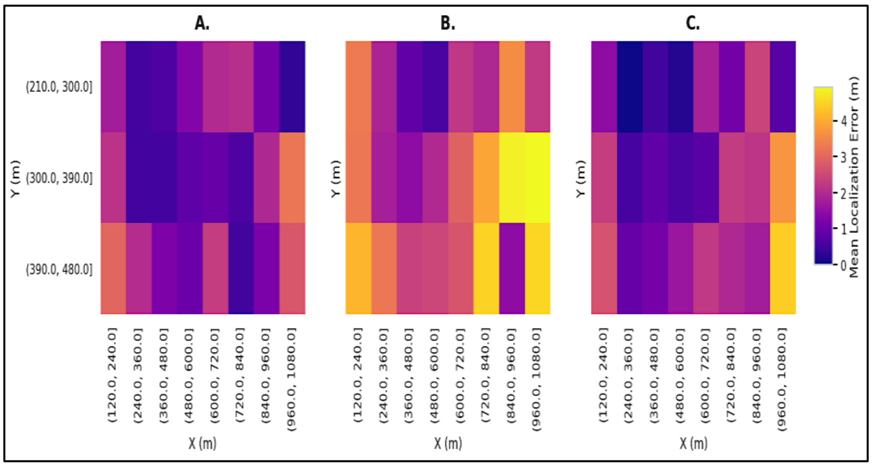

Figure 7: Model-wise Spatial Localization Heatmap– A. RF B. MLP C. KNN

The scatter plot in Figure 8 (A-D) shows that RF's predicted coordinates are closely clustered around a ground-truth coordinate. Further, suggesting that RF is highly spatially aligned and has very little dispersion. "RF has lower spatial dispersion compared to both MLP and KNN and has much lower Localization of error."

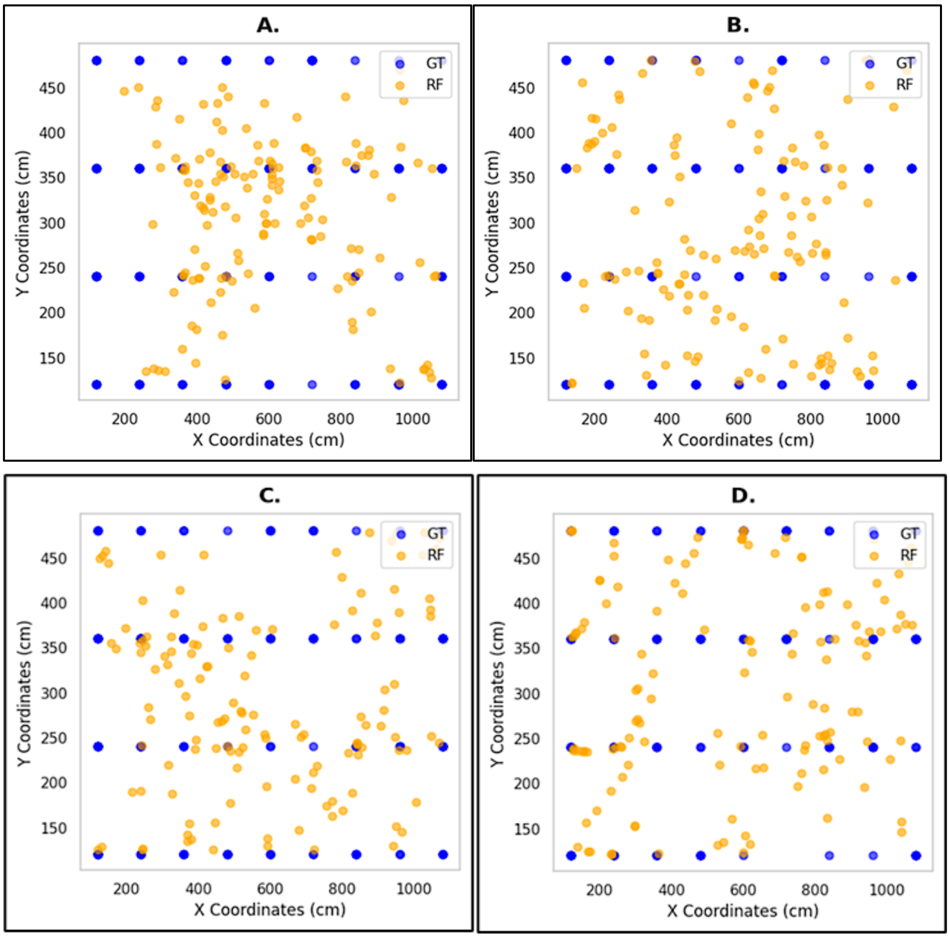

Figure 8: Random Forest Orientation Predicted Location vs GT– A. North B. South C. East D. West

The experimental results show how much fingerprint-based indoor localization performance depends on how the device is held. The mean, median, and upper percentile values of error differences all show that orientation plays an important role in the accuracy of localization. A comparison of errors also indicates that there is greater variability in errors due to orientation, particularly in the North and South direction. The Wilcoxon signed-rank test was used to confirm that there is a statistically significant difference ($p < 0.05$) in localization performance depending on the orientation of the device. These experiments demonstrated that there is a measurable difference in localization results based on the device orientation. Compared to the other models tested, Random Forest has lower sensitivity to device orientation and thus has better performance in the new proposed framework.

Discussion

The results provide evidence that device orientation affects BLE 5.1 fingerprint based indoor localization performance. Our results are similar to those from previous studies that showed large variations in signal from WiFi or BLE due to body interfering (shadows) and where the receiver's antenna is pointed relative to where it receives a signal (34). Most traditional fingerprinting approaches use a fixed direction of receiving a signal (assume that the receiver will always point in the same direction), or they do not consider the variations in the models of location based on a certain level of accuracy (35, 36).

The reduced localization error observed when the device is East and West (E/W) oriented indicates that the alignment of the antenna of the device and that of the anchor nodes reduces the effects of body shadows and obstruction. In contrast, the greater localization errors obtained for the North and South (N/S) orientations indicate that there are increased attenuation and multipath distortion, both of which reduce the stability of the RSS and degrade the accuracy of the AoA estimates. The results of this study support previous research which indicates the variability in performance due to the distortion of signal characteristics from human body shadowing and the radiation patterns of antennas (37). These types of effects due to orientation have been largely overlooked in traditional BLE fingerprinting studies. The results demonstrate that orientation has an impact on both average error and reliability, as evidenced by the additional deviations in error above the upper percentiles. In addition, the results show that, rather than being independent of the device's orientation, spatial errors will occur consistently between locations when using BLE fingerprints to determine their final positions.

From a modeling perspective, the Random Forest algorithm performed robustly in all orientations due in part to its ensemble component and ability to model nonlinear signal variations. Such a similar result in Sensors where the ensemble and deep learning methods outperformed traditional machine learning methods for BLE localization tasks (38). The finding that radio frequency (RF) can effectively decrease variance as a result of trees being aggregated into one location also explains why the RF performed consistently across all orientations during this study. The KNN demonstrated accuracy that was competitive in E/W orientations, but was more sensitive to changes in the orientation of the device. The performance of the MLP model was likely weaker due in part to the limited amount of data, which could affect the generalization of neural networks in indoor environments, and because of the susceptibility of neural networks to noise. The conclusion is that orientation must be specifically considered when developing practical systems for fingerprint-based indoor localization.

These results confirm the need for orientation-aware modeling techniques when developing effective BLE indoor localization systems more important.

Conclusion

This research investigated the effects of different device orientations on the accuracy of indoor localization using BLE 5.1 fingerprinting. A BLE fingerprinting system was created to use RSS and AoA data, and utilize several regression machine learning algorithms to predict location information on a person whose device had been fingerprinted and a target person whose device had not been fingerprinted through RSS and AoA measurements. Four experiment trials were run to determine whether localization performance (accuracy) for the three algorithms tested (Random Forest, KNN, and MLP) varied with both an individual's body and their device being in either portrait or landscape orientation. The results of the study using a publicly available static dataset for localization demonstrated that localization performance (accuracy) is impacted by body-device (physically) orientation and is, therefore, orientation dependent. The study also demonstrated that Random Forest was consistently provides better results across all orientations and KNN was close behind, while MLP consistently shown lower ability to generalize.

Results support the theory that the orientation of the body in relation to the device generates unique fingerprints that affect localization accuracy and therefore, system designers should take into account, while designing a BLE fingerprinting system for indoor localization, body-device physical orientation. Additionally, this research provides a body of empirical evidence that supports using orientation-aware modelling for effectively and ultimately reliably localising individuals indoors in a fixed usage area.

Future Directions

Future enhancements to the framework will incorporate dynamic and mobile user movements in order to assess real-time tracking capabilities. The addition of orientation-invariant features, orIMU that involve sensor fusion techniques, will help eliminate the effect of body shadows. The use of more advanced deep learning architectures (Convolutional Neural Networks (CNN) and Transformers) could also provide more accurate representations of spatial signal patterns.

Abbreviations

AoA: Angle of Arrival, BLE: Bluetooth Low Energy, CDF: Cumulative Distribution Function, GT: Ground Truth, IPS: Indoor Positioning System, KNN: K-Nearest Neighbour, MLP: Multilayer Perceptron, RF: Random Forest, RSS: Received Signal Strength.

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Author Contributions

Kowsalya P: Conceptualization, Data Collection, Data Analysis, Writing, Venkateswari P: Conceptualization, Supervision, Suggestions, Finalizing Paper, Rajakumar R: Conceptualization, Suggestions, Rajesh K: Conceptualization, Suggestions.

Data Availability

Data are available from the corresponding author upon reasonable request.

Conflict of Interest

The authors declare no conflict of interest.

Declaration of Artificial Intelligence (AI) Assistance

Artificial intelligence tools were used for language editing purposes only, while all analyses and results were performed by the authors.

Ethics approval

Not Applicable.

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