A WiFi RSS-RTT indoor positioning system using dynamic model switching algorithm

Xu Feng, Khuong An Nguyen, Zhiyuan Luo

***Abstract*— The advances in WiFi technology have encouraged the development of numerous indoor positioning systems. However, their performance varies significantly across different indoor environments, making it challenging in identifying the most suitable system for all scenarios. To address this challenge, we propose an algorithm that dynamically selects the most optimal WiFi positioning model for each location. Our algorithm employs a Machine Learning weighted model selection algorithm, trained on raw WiFi RSS, raw WiFi RTT data, statistical RSS & RTT measures, and Access Point line-of-sight information. We tested our algorithm in four complex indoor environments, and compared its performance to traditional WiFi indoor positioning models and state-of-the-art stacking models, demonstrating an improvement of up to 1.8 meters on average.**

***Index Terms*— Indoor fingerprinting, WiFi Round-Trip Time, Model switching.**

I. Introduction

WiFi fingerprinting has emerged as a leading approach for infrastructure-free indoor positioning, thanks to its capability to capture intricate nuances of the WiFi signal attenuation in different complex locations within a building. However, since fingerprinting heavily relies on the measurements of the WiFi signal, similar WiFi measurements recorded at far away location would result in a large prediction error. The current popular WiFi signal metrics for indoor positioning include Received Signal Strength (RSS) [1]–[3], Channel State Information (CSI) [4]–[6], and Round-Trip Time (RTT) [7]–[9]. Each of these measures has its own set of strengths and weaknesses. For instance, RTT excels in clear line-of-sight scenarios but lacks stability over a long time period, while RSS performs optimally in heavily attenuated non-line-of-sight conditions; CSI has the potential for fine-grained positioning, but is not yet widely supported by most hardware.

To address this challenge, we propose a novel algorithm designed to select the most optimal indoor positioning model for each specific location. The idea of the proposed algorithm is not to find a universally, applicable and efficient solution for every location but, alternatively, to automatically recommend the optimal location predictor. Our algorithm incorporates a weighted model selection technique that dynamically assigns varying weights based on the unique signal characteristics of each location. Designed for implementation on heterogeneous devices, especially smartphones, our focus lies on utilising the WiFi RSS and RTT signal measures as input features, given that CSI is not yet readily available on commercial WiFi Access Points (APs) and smartphones. The input features for the proposed algorithm include the WiFi RSS and RTT signal measures, the RSS and RTT statistical features, and the Line-of-Sight (LOS) information [9].

Xu Feng, Khuong An Nguyen and Zhiyuan Luo are with the Computer Science Department, Royal Holloway University of London, Surrey, TW20 0EX, United Kingdom (e-mail: Xu.Feng.2023@live.rhul.ac.uk).

The performance evaluation involves a comprehensive comparison against four traditional WiFi-based indoor positioning models, and state-of-the-art Machine Learning and Deep Learning stacking algorithms, on four real-world testbeds collected in diverse and complicated scenarios with varying WiFi conditions, including Line-of-Sight (LOS), Non-Line-of-Sight (NLOS), and mixed LOS-NLOS scenarios.

A. Paper's contributions

Our contributions are as follows:

- We propose an algorithm designed to dynamically select the most optimal indoor positioning model in real-time for each location.
- We assess the performance of our algorithm on four datasets collected from challenging real-world indoor scenarios under different WiFi conditions (i.e., LOS, NLOS and mixed LOS-NLOS).
- We openly share our indoor positioning datasets, meticulously gathered in a campus building, containing both WiFi RSS and WiFi RTT signal measures, as well as correct LOS condition of all APs at every location.

The rest of the paper is organised as follows. Section II introduces the related work in WiFi-based indoor positioning and Section III formulates the WiFi-based indoor fingerprinting problem. Then, the proposed weighted model selection algorithm is described in Section IV. Section V discusses the experimental setup and the results of the empirical evaluation. Finally, Section VI concludes the paper.

II. Related Works

As one of the most widely used signal measures, WiFi RSS plays a pivotal role in many fingerprinting-based systems [10]–[15]. In [16], particle swarm optimisation (PSO) was applied to enhance RSS-based performance. Mahalanobis distance, rather than Euclidean distance, was utilised by [17] to make positioning estimations based on RSS fingerprinting. To mitigate the disturbance of RSS measures, [18] projected the RSS features into the improved probabilistic linear discriminant analysis

(PLDA) latent space to achieve an average accuracy of 1.38 metres.

Introduced by the IEEE 802.11n standard, CSI has received widespread attention in indoor positioning [5], [19]–[21]. The system in [22] used a combined CNN and LSTM network for CSI fingerprinting. To mitigate the instability of RSS signal measures, a hybrid method using RSS and CSI was proposed by [23] based on Weighted K-Nearest Neighbours (WKNN). In [24], CRISLoc, a CSI fingerprinting system, was proposed by employing transfer learning and an enhanced KNN. Furthermore, a novel CSI signal fingerprinting method was proposed in [25] to achieve decimetre-level accuracy. However, the implementation of these CSI-based systems on commercial smartphones remains a major challenge.

Recently introduced in the IEEE 802.11-2016 standard, RTT promised to deliver sub-metre level accuracy for indoor positioning [8], [26]. The authors in [8] proposed a particle filter-based indoor positioning algorithm. A novel method proposed by [27] fused RTT and smartphone microelectromechanical sensors for accurate indoor quadrotor localisation. In [28], an RTT compensation distance network (RCDN) and a region proposal network (RPN) were utilized to address the challenge of NLOS. To better enhance the performance, a fusion method of UWB, WiFi RTT and WiFi RSS was developed by [29]. The authors of [30] presented a tightly coupled fusion platform using RTT, RSS and data-driven pedestrian dead reckoning (PDR) to achieve an accuracy of 0.39 metres. However for a complex indoor environment, the best possible positioning model for each location remains a research question. Therefore, a weighted best positioning model selection algorithm is proposed to address this challenge.

To enhance the performance of indoor positioning systems, various hybrid approaches combining multiple technologies were proposed in the literature. In [31], [32], optimal AP selection using Particle Swarm Optimization was leveraged to enhance the perceptibility of WiFi-based indoor localization, enabling scalable solutions with reduced maintenance costs. The proposed feature-based ensemble model, trained on selected AP subsets, achieves high accuracy (86%–96%) and a significant reduction the number of APs (50%–65%), yielding a mean absolute error of 2.68 metres. The authors in [33] presents an indoor pedestrian location scheme utilizing UWB/PDR and Floor Map data. The proposed approach includes a robust UWB positioning algorithm addressing ill-conditioned positions, a heading angle-computed strategy for PDR mapped to Floor Map directions, and an Extended Kalman Filter fusion for UWB/PDR/Floor Map, demonstrating reliable decimeter-level positioning in the experimental scenarios. A Kalman filter was applied by [34] to combine PDR system using accelerometer, gyroscope, magnetometer and WiFi RSS trilateration. By analyzing WiFi signal strength to overcome PDR drift errors and using PDR results to compensate for WiFi signal fluctuations, the proposed algorithm demonstrated high position accuracy, achieving an improved average localization accuracy of 1.6 meters. UWB, GPS and magnetic, angular, gravity and gravity were fused in [35] by a weighted fusion algorithm. In [36], [37], 2.4G and 5G WiFi RSS measures were used by both SVM and Capsule network in a fuse learning method for location estimation. The system proposed by [38] used an error state extended Kalman filter to fuse a 5G network CSI and magnetometer based back propagation neural network, and a visual inertial odometry for indoor localisation.

Ensemble learning, leveraging multiple base models, was proposed to achieve more robust indoor positioning performance. An ensemble filter was leveraged by [39] to generate final positioning predictions from Bluetooth Low Energy based KStar, Random Forest and a Decision Tree. The system in [40] introduced a crowdsourcing approach called AAIFU (Automatic Altered APs Identification and Fingerprints Updating). AAIFU adopted a Gradient Boosting Decision Tree (GBDT) to make WiFi RSS fingerprinting based on crowdsourcing radio map. The authors in [41], [42] proposed a weighted ensemble classifier based on Dempster–Shafer belief theory to efficiently handle diverse contexts, defined by smartphone configurations and temporal signal variations. Their real-life experiments on JUIndoorLoc and UJIIndoorLoc datasets demonstrated the effectiveness of the technique, achieving up to 98% localization accuracy in scenarios with varying training and testing conditions. To achieve better positioning accuracy on smartphones, [43] proposed a deep learning ensemble classifier that utilised three magnetic based neural networks' predictions and the information from accelerometer and gyroscope. WiFi CSI measure was leveraged by [44] to train multiple base models. They employed a stacking ensemble broad learning system. Then, the use of a bootstrapping method for training set construction, coupled with the advantages of the broad learning system as a base learner, resulted in improved accuracy in both LOS and NLOS environments. The method proposed by [45] combined DNN features and GBDT features for more accurate WiFi fingerprinting.

Stacking is a specific technique within ensemble learning that leverages the positioning predictions from different primary learners as the input to train a secondary learner for final estimation. The authors in [46] introduced TreeLoc, an improved localization method for wireless indoor localization, focusing on RSS and utilizing ensemble learning trees. The method, employing Decision Tree Regressor (DTR), Random Forest Regression (RFR), and Extra Tree Regressor, demonstrated superior performance in position estimation for indoor environments. TreeLoc achieved an RMSE of 8.79 for the x-coordinate and 8.83 for the y-coordinate. To maintain accuracy, [47] proposed a WiFi-based stacking framework that leveraged the predictions from AdaBoost, Random Forest, and Kernel Ridge to train a secondary learner for stack model predictions. A robust and time-independent WiFi fingerprint was generated by learning the reconstruction distribution from raw and artificially noised WiFi signals. Leveraging the powerful representation capabilities of MLP (Multi-Layer Perceptron), the authors built a regression model that accurately mapped the extracted features to corresponding locations.

The system proposed by [48], [49] used CNN, SVM, ELM, and XGBoost as the primary learner and stacked a XGBoost as the secondary learner for WiFi fingerprinting positioning. To mitigate the "dimensional disaster" caused by hundreds of APs in WiFi fingerprint databases, the authors employed a random forest for feature selection and an improved deep autoencoder for extraction. Multiple machine learning models, including SVM, XGBoost, and ELM, were fused using a Stacking model to deliver a floor prediction accuracy of 95.13%. A detailed comparison of the related works is shown in Table I.

However, most methods in the literature so far have only focused on fusing different technologies or using multiple base models to make the final prediction. This process involves a considerable computational demand and highly relies on multiple pre-installed signal transmitters. To address this limitation, we propose a dynamic model switching algorithm for WiFi indoor positioning that only requires existing commercial APs.

III. Problem Formulation

To formulate the problem, the indoor environment is divided into a total number of N locations. At each location $P_i, (i = 1, 2, \dots, N)$, a fixed number of WiFi scans is performed to collect the RSS and RTT measurements from J number of nearby APs. The fingerprinting database is defined as:

$$X = \{RSS_{i1}, \dots, RSS_{iJ}, RTT_{i1}, \dots, RTT_{iJ}\}_{i=1}^{N} \tag{1}$$

where i is the indicator of a specific location, and J is the total number of APs in the environment. To provide a more comprehensive understanding of the WiFi signal propagation, statistical features (i.e., Mean (μ), median (Med), standard deviation (σ), Skewness ($\mathcal{S}$) and Kurtosis ($\mathcal{K}$)) of WiFi RSS and RTT signal measures are extracted and merged with X to form a new input feature set, defined as:

$$\mathcal{X} = \{\mu, Med, \sigma, \mathcal{K}, \mathcal{S}, X\} \tag{2}$$

In the proposed algorithm, several popular WiFi indoor positioning models are leveraged to perform preliminary positioning estimations based on the input WiFi signal features. The label indicating the ground truth location of each location is defined as a vector

$$Y_{loc} = \{y_i\}_{i=1}^{N} \tag{3}$$

where y_i contains the real-world coordinates of the i^{th} location. The positioning estimation from these models is defined as:

$$Y_{loc\_test} = \{y_{i1}, y_{i2}, \dots, y_{iM}\}_{i=1}^{N} \tag{4}$$

where M is the total number of preliminary indoor positioning models.

Next, the best positioning model b_i for each location P_i is determined by comparing Y_{loc_test} to Y_{loc}. Then, the original WiFi RSS and RTT signal measure and their statistical features $\mathcal{X}$ and the preliminary positioning results Y_{loc_test} are combined altogether as input features for the weighted model selection algorithm. The hidden correlations between $\mathcal{X}$ and Y_{loc_test}, and B_{priori} are learned by a random forest classifier (RFC) in the weighted model selection algorithm, where $B_{priori} = \{b_i\}_{i=1}^{N}$, $b_i \in \{1, ..., M\}$.

When the user at an unknown location reports their real-time new WiFi signal measurements $X_{test} = \{RSS_{test1}, \dots, RSS_{testJ}, RTT_{test1}, \dots, RTT_{testJ}\}$, our model automatically selects the features with the strongest correlations and predicts the optimal indoor positioning model b_{test} for the test location. Finally, the positioning estimation of the user's current location is made by the selected model b_{test}.

IV. System architecture

To automatically select the best possible location predictor for each location in the environment, our system consists of 5 steps (see Figure 1). They are Data Preprocessing, Data Preparation, Preliminary Positioning, Weighted Model Selection and Performance Validation.

- Step 1: We preprocess the raw WiFi signal data by firstly removing outliers in the RSS and RTT signal measures. Next, we replace the missing WiFi RTT and RSS measurements with default values, indicating that such AP was not visible at the current location. Then, we utilise One-Hot Encoding to reformat the LOS information of all APs for the current location.
- Step 2: Statistical feature extraction is leveraged to produce statistics of the WiFi RSS and RTT measures.
- Step 3: Four popular indoor positioning models are leveraged to deliver the preliminary positioning estimations. They are WiFi RTT trilateration, WiFi RSS fingerprinting, WiFi RTT fingerprinting, and hybrid RSS-RTT fingerprinting.
- Step 4: The outputs from the previous step are merged with original WiFi RSS and RTT signal measures, WiFi RSS and RTT statistical features, and LOS conditions of all APs to create a new set of input features. Then, the input features are fed into the weighted model selection algorithm where the most informative features to determine the most suitable positioning model are selected.
- Step 5: Given a new WiFi sample reported at an unknown location, a feature preprocessing method is used for data cleaning. Then, the preprocessed model automatically selects the best positioning model, and the final location estimation is generated.

We will discuss each step in detail in the following sections.

A. Data preprocessing and data preparation

In this initial preprocessing step, we preprocess the raw WiFi signal data to remove outliers, and fill in missing WiFi RTT and RSS measurements with default values of -200 dBm for RSS entries and 100 m for RTT entries, to indicate that the corresponding AP was not visible at the current location.

To streamline the data representation, One-Hot Encoding technique was employed to reformat the LOS conditions for all APs present in the given location. Since LOS condition is critical to WiFi based indoor positioning performance, integrating such information provides more informative features for the best model selection. The impact of NLOS condition to the WiFi RSS and RTT signal measures are shown in Figure 2 [9]. A snapshot of the preprocessed input WiFi signal measurements with LOS conditions of all present APs is shown as Table II (a) and (b).

Next, to gain a comprehensive insight into the WiFi propagation characteristics, a feature extraction method was leveraged to generate the statistical features from the WiFi RSS and

TABLE I: Comparison of the performance of notable work in combining, ensemble and stacking indoor positioning systems.

Reference	Input Features	Performance	Description
[31]	WiFi RSS Radio Map	2.68 m	The system utilized a feature-based ensemble model, for indoor positioning.
[33]	UWB, PDR, Floor Map	0.15 m, in X direction	The system integrated a robust algorithm, a heading angle-computed strategy, and an Extended Kalman Filter fusion algorithm.
[34]	WiFi RSS, PDR	1.6 m	The system utilized a sensor fusion framework that combined WiFi signal strength and PDR data to address signal fluctuations and drift errors.
[35]	GPS, UWB, Magnetic field	3.2 m	The proposed system employed a weighted fusion algorithm to seamlessly position in cross-region and complex environments.
[36]	WiFi RSS	0.99 m	The system combined WiFi 2.4G and 5G signals through an SVM model and capsule networks to improve indoor localization accuracy.
[38]	5G CSI, geomagnetism, VIO	0.61 m	The system used an error back propagation neural network and an error state extended Kalman filter for signal combination.
[39]	BLE beacon-based data	2 m	The study utilised an ensemble filter to achieve a more accurate consumer localization.
[40]	WiFi RSS	2.6 m	The system introduced a crowdsourcing indoor positioning approach based on ensemble learning.
[41]	WiFi RSS statistics	98%, location estimation	The system introduced a weighted ensemble classifier effectively for handling context heterogeneity caused by varying smartphone configurations and temporal signal variations.
[43]	magnetic field	2.23 m	The system utilized a deep neural network-based ensemble classifier to address device heterogeneity in indoor localization.
[44]	WiFi CSI	1.15 m	The system was a stacking ensemble broad learning localization system using channel state information as a fingerprint.
[45]	WiFi RSS	0.77 m	The system employed a feature extraction algorithm to address the volatility and high-dimensional sparseness of WiFi data, and integrated these features to a hybrid model.
[47]	WiFi RSS	4.24 m	The system utilized an SDAE-based feature extraction method to handle dynamic WiFi signal fluctuations and sparsity, generating robust and time-independent WiFi fingerprints.
[48]	WiFi RSS	95.13%, floor identification	The system employed a feature selection process with a random forest algorithm, followed by an improved deep autoencoder for feature extraction.

RTT measures. Mean (μ), median (Med), standard deviation (σ), Skewness ($\mathcal{S}$) and Kurtosis ($\mathcal{K}$), which were reported to be the most informative features for LOS identification [50], are computed from the raw input WiFi RSS and RTT measures, as follows:

$$\mu = \frac{\sum_{k=1}^{K} x_k}{K} \tag{5}$$

$$\mu_m = \frac{\sum_{k=1}^{K} (x_k - \mu)^m}{K} \tag{6}$$

$$\sigma = \sqrt{\mu_2} \tag{7}$$

$$\mathcal{S} = \frac{\mu_3}{\sigma^3} \tag{8}$$

$$\mathcal{K} = \frac{\mu_4}{\sigma^4} \tag{9}$$

where x_k is the RSS or RTT measurements collected at a specific location, and K is the total number of data samples. μ_m denotes the m^{th} central moment. Intuitively, Kurtosis measures the peakedness of the measurements distribution, describing the tails' relative weight to the distribution's center, and Skewness quantifies the asymmetry of the measurements distribution, indicating whether the data distribution is skewed to the left or right. A snapshot of the statistical features of the input WiFi signal measurements is shown as Table II (c) and (d). Then, the statistical features of the input WiFi RSS and RTT data were merged together with the preprocessed WiFi RSS and RTT signal measures, and LOS conditions of all present APs, and were fed into the next step for preliminary positioning estimation evaluation.

B. Preliminary positioning

Following on from the preprocessing and preparation step, we employ 4 popular indoor positioning models to derive the preliminary position estimations. They are WiFi RSS fingerprinting, WiFi RTT fingerprinting, hybrid RSS-RTT fingerprinting, and WiFi RTT trilateration techniques. This diverse set of WiFi indoor positioning models provide preliminary positioning results to be leveraged in the next step for the best positioning model selection, namely $\{RSS_x, RSS_y, RTT_x, RTT_y, RTT + RSS_x, RTT + RSS_y, Trilateration_x, Trilateration_y\}$.

C. Weighted model selection algorithm

The preliminary positioning estimations from the popular WiFi indoor positioning models, as described in the previous step, are merged together with WiFi signal measures and statistical features and served as input for our innovative weighted

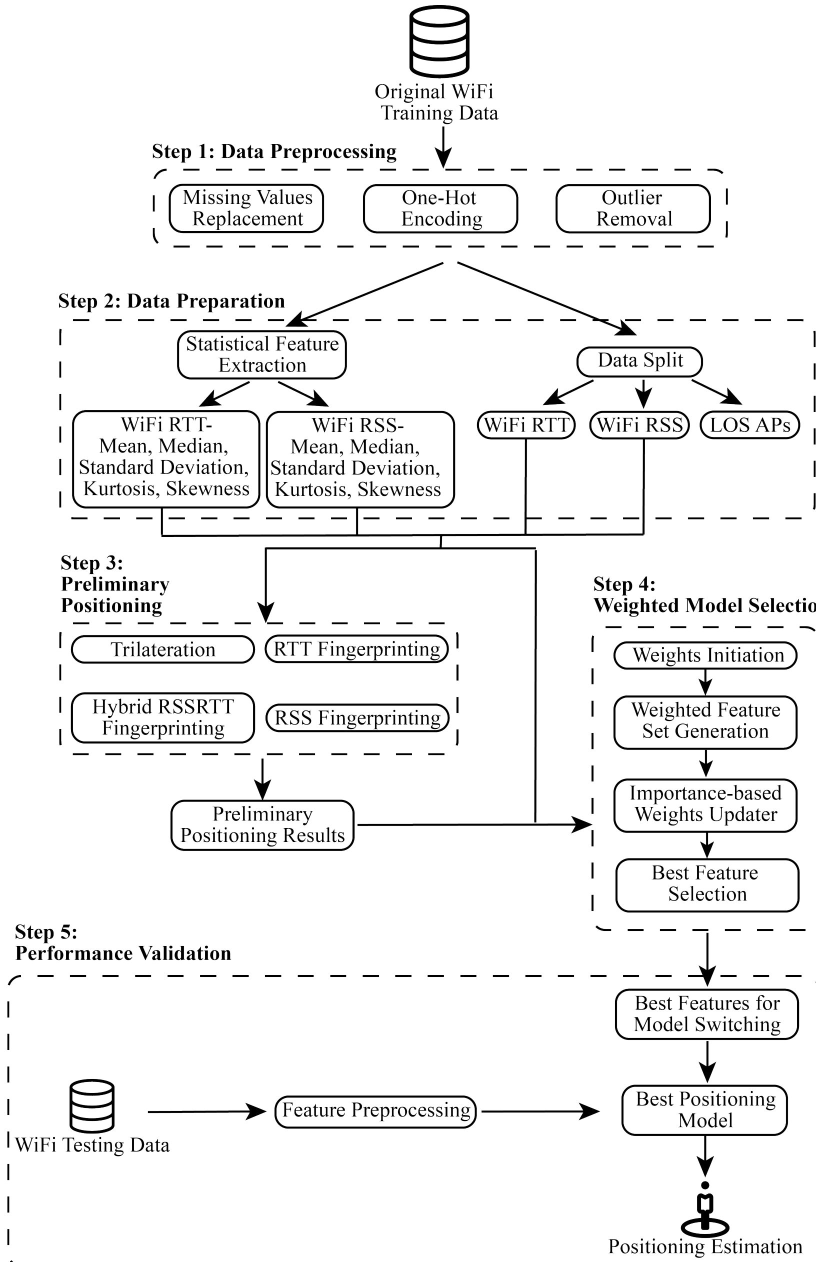
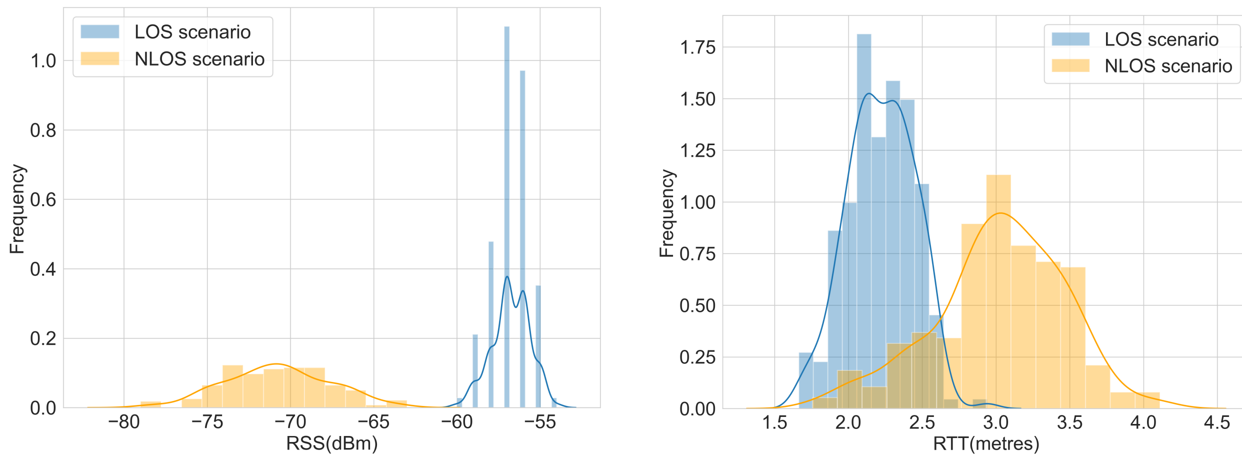


Fig. 1: The architecture of our proposed system. Note that LOS information was not incorporated in both training and testing phases.

model selection algorithm. Figure 1 and Algorithm 1 provide a comprehensive overview of the weighted model selection process, which encompasses weight initiation, weighted feature set generation, importance-based weights updater, and the best feature selection for final model switching. The selected feature set will be utilised for choosing the most optimal positioning model for any new WiFi test sample.

The selection and refinement of the most informative feature set are integral to our algorithm, optimising efficiency and accuracy for diverse locations. It mitigates high dimensionality challenges, ensures computational efficiency, and enhances model performance by focusing on the most informative features. For example, different patterns hidden in the input WiFi original signal and statistical features have a strong correlation to choosing between RTT fingerprinting and RSS fingerprinting for a specific location where most APs were under NLOS conditions. This adaptability allows the algorithm to cater for location-specific characteristics in complex indoor spaces, leading to robust model selection and improved generalisation. Overall, this strategic approach balances accuracy and computational efficiency.

Upon the integration of the preliminary positioning results, the preprocessed WiFi RSS and RTT signal measures, and WiFi signal statistical features into the weighted model selection algorithm, the initial weights are systematically established for each input feature, signifying their respective significance in determining the user's location. This weight initiation process employs the mean absolute error (MAE)



(a) WiFi RSS signal distribution under LOS and NLOS conditions.

(b) WiFi RTT signal distribution under LOS and NLOS conditions.

Fig. 2: The WiFi RSS and RTT signal measures vary significantly under LOS and NLOS scenarios. The smartphone was set 3 metres away from the WiFi AP. A person was standing between the smartphone and the AP to create the NLOS condition. Under NLOS condition, WiFi RSS measurement became unstable and weaker drastically, while WiFi RTT measurement became larger, more unreliable and further away from the ground truth measure.

as the metric to evaluate the performance of the preliminary models obtained in the prior step. A smaller MAE indicates a more accurate model. The weight ($w^{(m)}$) assigned to the m^{th} model ($m \in \{1, 2, \ldots, M\}$) is defined as:

$$w^{(m)} = \frac{E^{(m)}}{\sum_{i=1}^{M} E^{(i)}} \tag{10}$$

$$E^{(m)} = \frac{n}{|Y^{(m)}_{loc\_test} - Y_{loc}|} \tag{11}$$

where n indicates the length of the ground truth coordinates of each location Y_{loc}, M is the total number of positioning methods, $Y^{(m)}_{loc\_test}$ and $w^{(m)}$ are the positioning performance and the weight of the features adopted by the m^{th} model, respectively.

Following the weight initiation process, each feature receives a weight denoting how strong its correlation is with the ground truth label. A subsequent step involves the generation of a new feature set, which includes the preliminary positioning model estimations, preprocessed WiFi RSS and RTT signal measures, WiFi signal statistical features, and their respective weights for the importance-based weights updater. The primary aim of the weighted model selection algorithm is to choose the most informative features for identifying the optimal positioning model for a new WiFi sample. Within the importance-based weights updater, the significance of each feature in predicting the best positioning model was assessed through Permutation Importance and Mean Decrease in Impurity, as detailed below.

Permutation Importance is a robust technique employed in feature importance assessment for machine learning models. It operates by evaluating the impact of individual features on a model's performance through systematic permutation of feature values. The procedure involves randomly shuffling the values of a specific feature and observing the consequent change in the model's performance metric, such as accuracy or mean absolute error. In every iteration within the Weighted Model Selection algorithm, the feature importance $w^{(m)}_{perm}[x]$ of a specific feature x in deciding the best possible positioning model for each reference point (RP) is defined as:

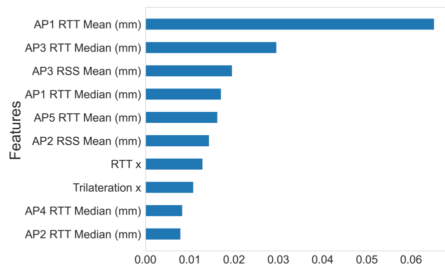
$$w^{(m)}_{perm}[x] = Score - Score_x \tag{12}$$

$$Score = Classifier(\mathcal{X}_{weigted}, B_{priori}) \tag{13}$$

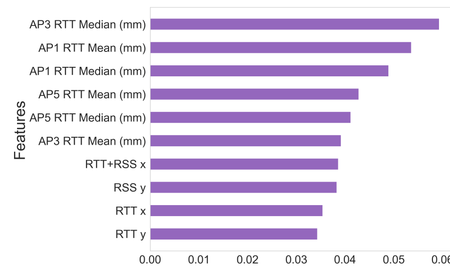
$$Score_x = Classifier(\mathcal{X}_{weigted\_shuffled}, B_{priori}) \tag{14}$$

where m indicates the m^{th} positioning model in the preliminary positioning step, $Classifier$ is the classifier trained for the best positioning model selection, $\mathcal{X}_{weigted}$ and B_{priori} indicate the input WiFi features and the ground truth best positioning model label to the classifier, $\mathcal{X}_{weigted\_shuffled}$ is the input feature set where feature x is randomly shuffled, and $Score$ and $Score_x$ evaluate the performance of the original and shuffled input feature set. By comparing the model's original performance with the performance under various permutations, it quantifies the significance of each feature in influencing the model's predictions. The feature importance $w^{(m)}_{perm}[x]$ provides a comprehensive understanding of how informative and crucial a specific feature is, aiding in the identification of best features contributing to the best positioning model prediction for each location.

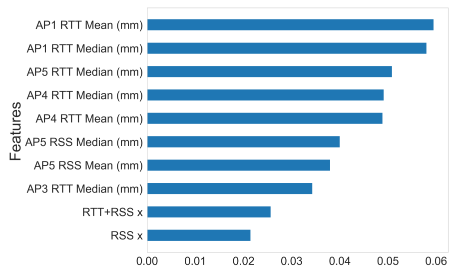
Figure 3 depicts the permutation importance analysis applied to the input feature set for optimal positioning model prediction. Features contributing positively to the prediction accuracy will be assigned higher importances and selectively incorporated by the proposed algorithm. The magnitude of positive importance corresponds directly to the significance of each feature within the weighted model selection algorithm. Larger positive importances indicate heightened importance, emphasising the influential role of specific features in the algorithm's decision-making process.



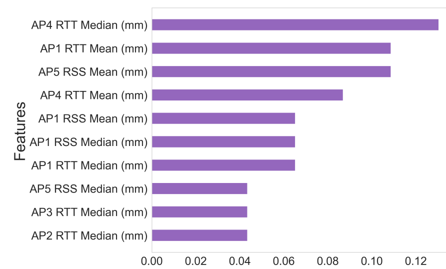
(a) Permutation importance of the statistical WiFi input of lecture theatre testbed.



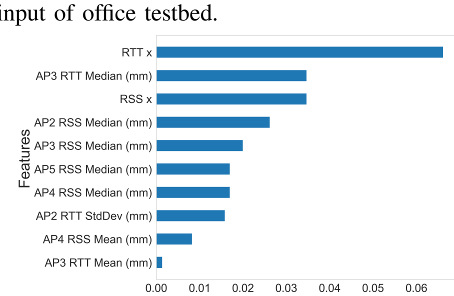
(b) Mean decrease in impurity of the statistical WiFi input of lecture theatre testbed.



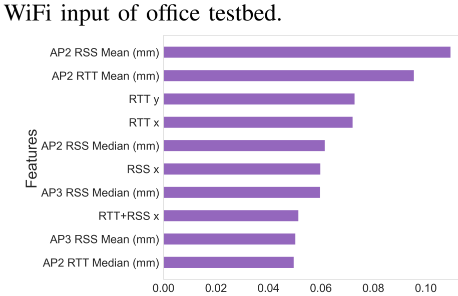
(c) Permutation importance of the statistical WiFi input of office testbed.



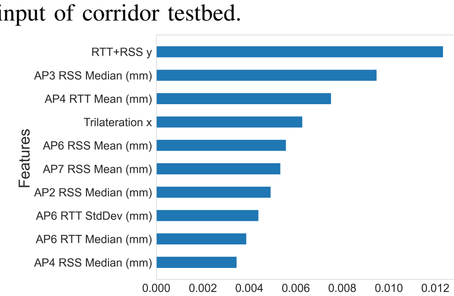
(d) Mean decrease in impurity of the statistical WiFi input of office testbed.



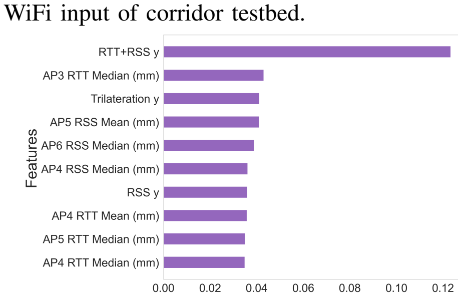
(e) Permutation importance of the statistical WiFi input of corridor testbed.



(f) Mean decrease in impurity of the statistical WiFi input of corridor testbed.



(g) Permutation importance of the statistical WiFi input of floor testbed.



(h) Mean decrease in impurity of the statistical WiFi input of floor testbed.

Fig. 3: The importance of the top 10 informative features in the input feature set from all four dataset. Larger importance means that the feature has a positive contribution to the final positioning prediction.

Mean Decrease in Impurity (MDI) is a popular metric for ensemble decision tree frameworks like Random Forests, to assess the significance of the input features. It quantifies the role of each feature in enhancing the model's prediction performance by evaluating its impact on reducing impurity or disorder across all decision trees in the ensemble. Impurity denotes the level of uncertainty or randomness inherent in the dataset. The MDI score $Score_{MDI}$ of feature x for random forest is defined as:

$$Score_{MDI,x,i} = \sum_{k=1}^{n_i} p_{k,i} \cdot \Delta I_{k,i}(x) \tag{15}$$

$$Score_{MDI} = \frac{1}{N_T} \sum_{i=1}^{N_T} Score_{MDI,x,i} \tag{16}$$

where $p_{k,i}$ is the proportion of training data that reach node k in tree i, n_i is the number of nodes in i, $\Delta I_{k,i}(x)$ is the decrease in impurity caused by splitting on feature x at node k in tree i, N_T is the total number of trees in the

TABLE II: A snapshot of our WiFi fingerprinting dataset.

(a) WiFi RSS data samples.

X	Y	AP1 RSS (dBm)	AP2 RSS (dBm)	…	AP5 RSS (dBm)	LOS APs
0.6	1.2	-51	-70	…	-81	1 2 4
1.2	0.0	-56	-68	…	-200	3 4
…	…	…	…	…	…	…
1.8	1.2	-61	-200	…	-72	2 3 4

(b) WiFi RTT data samples.

X	Y	AP1 RTT (mm)	AP2 RTT (mm)	…	AP5 RTT (mm)	LOS APs
0.6	1.2	1194	6307	…	16119	1 2 4
1.2	0.0	2754	7391	…	100,000	3 4
…	…	…	…	…	…	…
1.8	1.2	1561	100,000	…	15132	2 3 4

(c) WiFi RSS statistical features of AP_1.

X	Y	μ (dBm)	σ (dBm)	Med (dBm)	$\mathcal{K}$	$\mathcal{S}$
0.6	1.2	-50.8	0.4	-51.0	3.3	1.5
1.2	0.0	-57.6	0.5	-58.0	1.2	0.4
…	…	…	…	…	…	…
1.8	1.2	-64.0	1.4	-64.0	1.7	0.0

(d) WiFi RTT statistical features of AP_1.

X	Y	μ (mm)	σ (mm)	Med (mm)	$\mathcal{K}$	$\mathcal{S}$
0.6	1.2	1206.4	86.3	1154.0	1.3	0.3
1.2	0.0	2643.8	42.9	2644.0	1.6	0.2
…	…	…	…	…	…	…
1.8	1.2	1548.2	31.8	1533.0	1.4	0.2

Random Forest, $Score_{MDI}$ is the overall MDI importance score of feature x in the forest. An example of the MDI importance of the input feature set to the best positioning model selection is shown in Figure 3 (b) and (d). Features consistently contributing to impurity reduction exhibit elevated MDI values, underscoring their pivotal role in augmenting the model's accuracy. Essentially, MDI gives us valuable insights into the correlation between the diverse features and the ground truth label.

In the importance-based weight updater, the importance $w_{perm}^{(m)}[x]$ of each input feature x was utilised to update the initial weight $w^{(m)}$ from the weights initiation step. Only the features that gain higher positive importance in predicting the best positioning model for each RP are given higher weights in the weights updater step. Finally, an updated feature set is selected for best model identification.

In the performance validation step, a user at an unknown location reported a new WiFi test sample containing both WiFi RSS and RTT signal measures. After the data preprocessing and statistical feature extraction, the reformatted WiFi signal inputs were fed into the model switching algorithm. By integrating the final feature set decided by Weighted Model Selection, the algorithm automatically decided the best positioning model for the user and generated the positioning estimation accordingly.

Algorithm 1 Our proposed weighted model selection algorithm.

Input: X: input WiFi RSS, RTT measure, X_{test}: test samples Y_{loc}: ground truth coords label, $Models$: positioning models, MAE: Mean Absolute Error, RFC: Random Forest Classifier.
Output: $\mathbb{X}$: best feature set for dynamically switch models

```
for x in X do    ▷ x includes both RTT and RSS measures
    μ ←Mean(x)
    Med ←Median(x)
    σ ←Standard Deviation(x)
    S ←Skewness(x)
    K ←Kurtosis(x)
end for
𝒳 ← {μ, Med, σ, K, S, X}
M ← |PreliminaryPositioningModels|
for m = 1, 2, ..., M do
    model ← m^th model in Models
    Y^(m)_loc_test ← model(𝒳, Y_loc)
    E^(m) ← Len(Y_loc)/(|Y^(m)_loc_test − Y_loc|)
end for
for m = 1, 2, ..., M do
    w^(m) ← E^(m) / Σ_{m=1}^{M} E^(m)
end for
W ← Σ_{m=1}^{M} w^(m)
𝒳_weighted ← WeightedFeature(𝒳, Y_loc_test, W)
B_priori ← argmin[MAE({Y^(m)_loc_test}_{m=1}^{M}, Y_loc)]    ▷
    B_priori indicates the best model m for each reference point (RP)
for m = 1, 2, ..., M do
    Score = RFC(𝒳_weigted, B_priori)
    Initialise empty array w^(m)_perm
    for x in 𝒳_weigted do
        feature_temp ← x
        𝒳_weigted[x] ← shuffle(x)
        Score_x ← RFC(𝒳_weigted, B_priori)
        𝒳_weigted[x] ← feature_temp
        w^(m)_perm[x] ← Score − Score_x
    end for
    w^(m) ← WeightUpdate(w^(m), w^(m)_perm)
end for
W ← Σ_{m=1}^{M} w^(m)
𝕏 ← GenerateBestFeatureSet(𝒳_weighted, W)
return 𝕏
```

V. Experimental Setup and Empirical Results

This section validates the performance of our proposed algorithm on four publicly available datasets collected from real-world indoor scenarios with varying LOS and NLOS conditions. We first introduce the details of the datasets. Then, we compare the proposed algorithm with state-of-the-art WiFi based indoor positioning models, and Deep Learning ensemble and stacking algorithms.

A. Testbeds

To assess the performance of our proposed algorithm and its robustness across diverse scenarios, we collected 4 real-world indoor datasets: a long corridor, a lecture theatre, an office room, and a whole building floor. The corridor testbed, spanning over 35 × 6 m^2, created a NLOS scenario where no location had a LOS path to any APs (see Figure 4(a)). In contrast, the lecture theatre testbed covered more than 15 × 14.5 m^2, constituted a LOS environment where all RPs had a clear LOS path to all APs (see Figure 4(b)). The office room, occupying an area of 18 × 5.5 m^2, featured a mixture of LOS and NLOS conditions, ensuring that each RP had at least one

LOS AP (see Figure 4(c)). The whole building floor, with an area of 92 × 15 m^2 is a complicated real-world scenario with both LOS and NLOS conditions (see Figure 4(d)). Each testbed was meticulously divided into 0.6 × 0.6 m^2 grids, when collecting the WiFi signals to ensure non-overlapping amongst training and testing locations.

To ensure the generalisation and transferability of the proposed algorithm, we used off-the-shelf commercial WiFi APs and an LG G8X ThinQ smartphone to conduct the experiments. At each location, a total number of 75 WiFi scans (150 for the floor dataset) were performed. For trilateration purposes, the accurate 3D location of all APs were carefully recorded and verified. The ground-truth label and the LOS conditions of all APs at each location were manually recorded and verified by two human testers. A summary of the four datasets is shown in Table III. They are also publicly available at `https://github.com/Fx386483710/Dataset_for_Model_Selection`.

TABLE III: A summary of our 4 testbeds.

Data features	Lecture Theatre	Office	Corridor	Floor
Testbed (m^2)	15 × 14.5	18 × 5.5	35 × 6	92 × 15
Grid size (m^2)	0.6 × 0.6	0.6 × 0.6	0.6 × 0.6	0.6 × 0.6
Number of RPs	120	108	114	642
WiFi Samples per RP recorded	75	75	75	150
WiFi Samples per RP selected	60	60	60	120
All samples	7,200	6,480	6,840	77,040
Training samples	5,400	4,860	5,130	57,960
Testing samples	1,800	1,620	1,710	19,080
Signal measure	RTT, RSS	RTT, RSS	RTT, RSS	RTT, RSS
WiFi condition	LOS	LOS-NLOS	NLOS	LOS-NLOS

B. Evaluation metric

Given the impact of the complex indoor structures on the WiFi signals, the selection of the most effective indoor positioning model becomes location-dependent. To investigate the optimal positioning estimator for each location, we conducted experiments across all four datasets with 4 models: WiFi RSS fingerprinting, WiFi RTT fingerprinting, hybrid RSS-RTT fingerprinting, and RTT trilateration. Employing the root mean square error (RMSE) as the evaluation metric, we assessed the average disparity between the positioning estimation and the ground truth co-ordinate. RMSE quantifies the average magnitude of differences between predicted values and actual values, providing a measure of the positioning model's overall performance, defined as:

$$RMSE = \sqrt{\frac{1}{n}\sum_{i=1}^{n}(y_i - \hat{y}_i)^2} \tag{17}$$

where n is the number of test samples, y_i represents the actual coordinates of the testing location, $\hat{y}_i$ represents the predicted coordinates. It is worth noting that our testing and training locations were not overlapped.

C. Individual model performance results

Table IV provides an overview of the results, highlighting the best positioning model for each location.

In our observations across all four testbeds, RTT fingerprinting demonstrated superior performance, outperforming other models in more than 36% of the locations with WiFi RSS and RTT signal measures as input features (see Figures 5 and 6). Despite the sub-metre accuracy claim, RTT trilateration did not perform well in most locations. Surprisingly, in the mixed LOS-NLOS environments of the office, corridor and building floor testbeds, RSS fingerprinting surpassed RTT fingerprinting in certain locations. These findings shed light on the nuanced behaviour of different positioning models across diverse indoor scenarios.

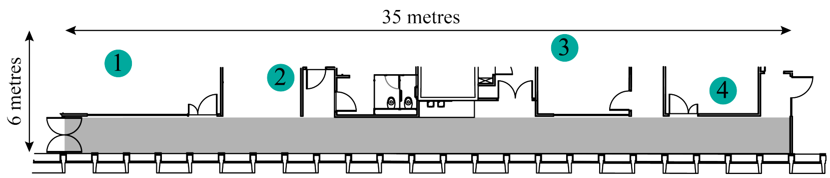
However, when investigating the positioning estimations based on WiFi statistical features, such as Mean, median, standard deviation, Skewness and Kurtosis, RTT fingerprinting performance decreased. In the corridor testbed where there was no LOS AP at all, statistical feature based RSS-RTT fingerprinting surpassed RTT fingerprinting by 9 locations, reaching 54 out of 114 locations. More interestingly, RTT trilateration based on mean RTT measurements had greatly improved its performance in the office testbed and building floor test bed (mixed LOS-NLOS scenarios), excelling in 20 more locations compared to the original WiFi measurements. We observed that incorporating the average value of RTT signal measures significantly contributed to the positioning accuracy of RTT trilateration in this mixed LOS-NLOS environment. Moreover, employing identical models with different WiFi input signal features led to variations in the best positioning model results for the same locations. These findings strongly suggested that there is not a universally superior positioning model across all scenarios. Therefore, the overall positioning accuracy could be improved by dynamically select the model based on the specific characteristics of each location.

D. Model selection performance results

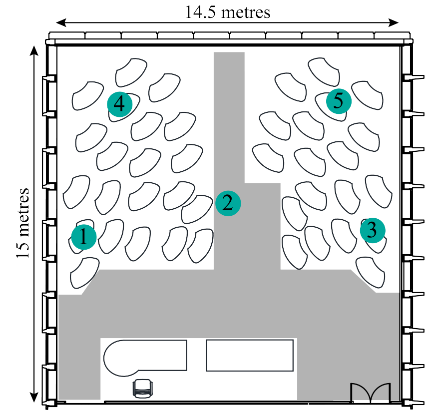
To evaluate the performance of our proposed model selection algorithm, we compare it with state-of-the-art Machine Learning and Deep Learning ensemble methods.

In-depth performance evaluation against state-of-the-art methods, specifically joint multi-task stacked denoising auto-encoder (JMT-SDAE) [45], random forest + SAE + Stacking (RS-stacking) [48], and the novel weighted ensemble classifier (NWEC) proposed by [41], revealed compelling outcomes, as detailed in Table V. Note that both RTT and RSS features were utilised by all the state-of-the-art models in the comparison. The comparative analysis in the office testbed, visualised through the cumulative distribution functions in Figure 7, showcased the superior performance of our algorithm.

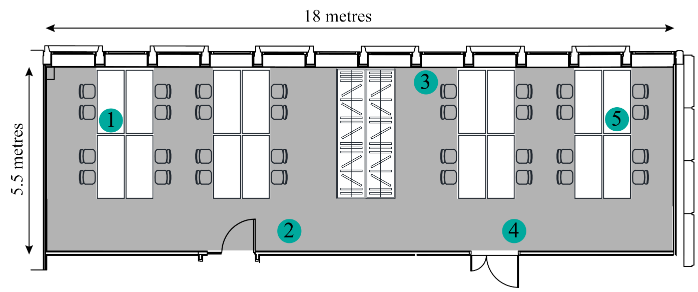
The proposed algorithm employed a machine learning weighted model selection algorithm, trained on raw WiFi RSS, WiFi RTT data, statistical RSS and RTT measures, and preliminary positioning estimations. Unlike state-of-the-art models that produced positioning predictions from multiple base classifiers' results, the essence of the proposed method lies in dynamically selecting the optimal WiFi positioning model for



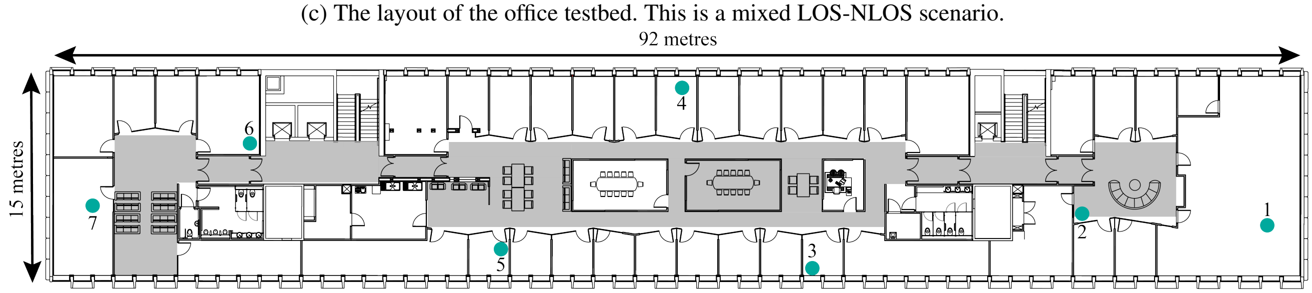
(a) The layout of the corridor testbed. This is a NLOS scenario.



(b) The layout of the lecture theatre testbed. This is a LOS scenario.



(c) The layout of the office testbed. This is a mixed LOS-NLOS scenario.



(d) The layout of the whole building floor testbed. This is a mixed LOS-NLOS scenario.

Fig. 4: The layouts of our 4 real-world indoor testbeds. The green dots indicate the APs' location. All WiFi measurements were collected in the grey area.

TABLE IV: The number of locations in which the positioning model performed best. It was interesting to observe that there was no clear dominant model for all locations.

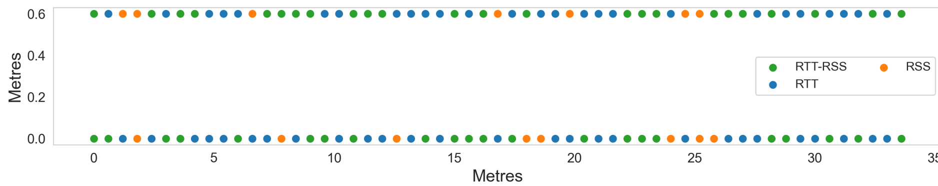
(a) Results based on original WiFi RSS and RTT signal measures.

Positioning model	Lecture Theatre (120 locations)	Office (108 locations)	Corridor (114 locations)	Floor (642 locations)
RTT trilateration	19	1	0	48
RSS fingerprinting	3	16	15	78
RTT fingerprinting	56	55	53	274
RSS-RTT fingerprinting	42	36	46	242

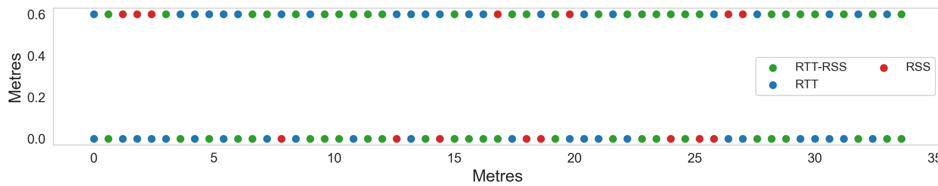
(b) Results based on WiFi RSS and RTT statistical features.

Positioning model	Lecture Theatre (120 locations)	Office (108 locations)	Corridor (114 locations)	Floor (642 locations)
RTT trilateration	18	21	0	65
RSS fingerprinting	6	15	15	46
RTT fingerprinting	56	43	45	232
RSS-RTT fingerprinting	40	29	54	299

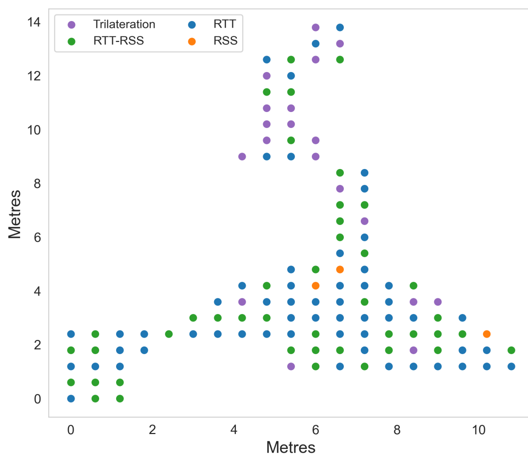
each location. The preliminary positioning estimations from basic positioning and fingerprinting models, and statistical features from WiFi RTT and RSS were utilised as input to the weighted model selection algorithm to predict the best WiFi



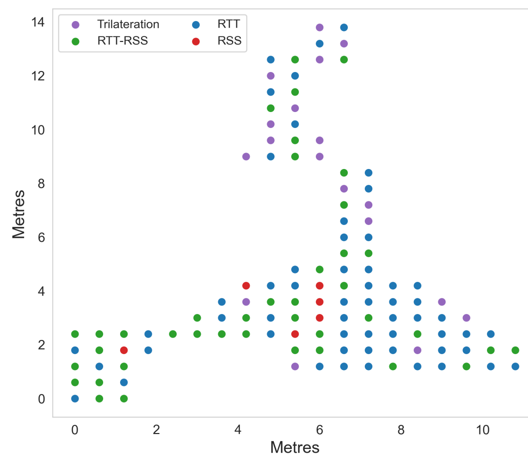
(a) The best positioning model for each RP in the corridor testbed based on the original WiFi signal measures. RTT fingerprinting excelled in 53 out of 114 locations.



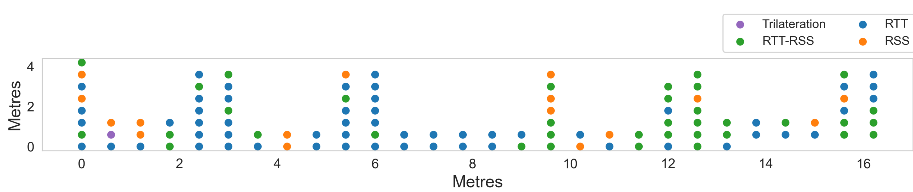
(b) The best positioning model for each RP in the corridor testbed based on the WiFi statistical features. RSS-RTT fingerprinting excelled in 54 out of 114 locations.



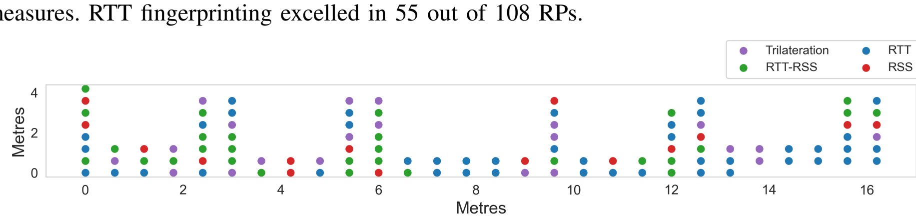
(c) The best positioning model for each RP in the lecture theatre testbed based on original WiFi signal measures. RTT fingerprinting excelled in 56 out of 120 RPs.



(d) The best positioning model for each RP in the lecture theatre testbed based on WiFi statistical features. RTT fingerprinting excelled in 56 out of 120 RPs.

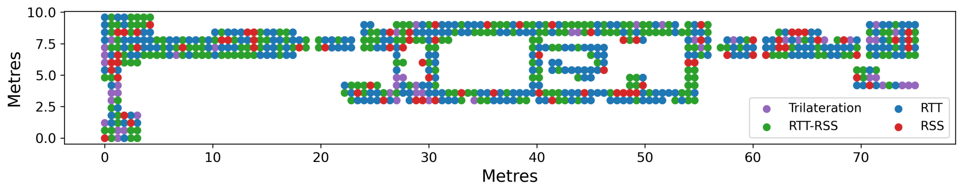


(e) The best positioning model for each RP in the office testbed based on original WiFi signal measures. RTT fingerprinting excelled in 55 out of 108 RPs.

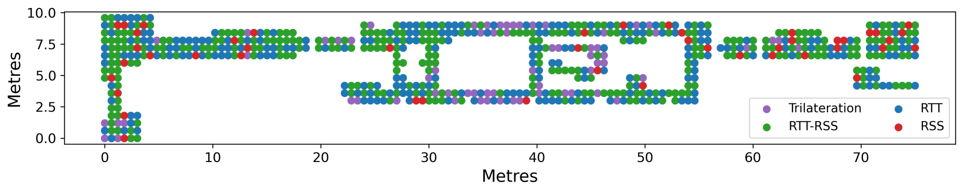


(f) The best positioning model for each RP in the office testbed based on WiFi statistical features. RTT fingerprinting excelled in 43 out of 108 RPs.

Fig. 5: The best positioning model for each location based on the original WiFi RSS and RTT signal measures and the WiFi statistical features. RSS fingerprinting based on the original measures are in orange while that based on statistical features are in red.



(a) The best positioning model for each RP in the floor testbed based on original WiFi signal measures. RTT fingerprinting excelled in 274 out of 642 RPs.



(b) The best positioning model for each RP in the floor testbed based on WiFi statistical features. RTT fingerprinting excelled in 232 out of 642 RPs.

Fig. 6: The best positioning model for each location based on the original WiFi RSS and RTT signal measures and the WiFi statistical features for floor dataset. RSS fingerprinting based on the original measures are in orange while that based on statistical features are in red.

positioning model for testing locations. Consequently, only the optimal basic positioning model is utilised at the final stage for estimation. This approach drastically reduces the complexity in generating the final positioning estimation while ensuring accuracy.

TABLE V: Performance comparison of the RMSE (m) of different models.

Model Name	Lecture Theatre	Office	Corridor	Floor
RSS-RTT fingerprinting	0.612	0.729	0.612	0.989
RTT fingerprinting	**0.559**	0.718	0.704	0.988
RSS fingerprinting	2.356	1.423	1.315	1.730
Trilateration	1.176	1.073	412.257*	7.503
JMT-SDAE	0.716	0.857	0.705	1.032
RS-stacking	0.724	0.824	0.672	0.967
NWEC	0.663	0.781	0.599	0.965
Proposed method	0.570	**0.698**	**0.569**	**0.935**

*Note that RTT measures from unseen APs were replaced by 100 metres.

Notably, our algorithm exhibited a remarkable up to 32% improvement in positioning estimation accuracy over state-of-the-art stacking algorithms. Additionally, it outperformed the standard WiFi RSS fingerprinting method by achieving a notable 1.8 meters reduction in RMSE. To assess the time efficiency of various algorithms in making predictions, we conducted evaluations using the entire building floor dataset. Our proposed algorithm demonstrated superior speed, requiring only 0.226 seconds, in stark contrast to JMT-SDAE, which took 0.567 seconds, RS-stacking, which utilized 0.890 seconds, and NWEC, which consumed 0.477 seconds. This superiority is attributed to our algorithm's ability to capture and leverage the nuanced information present in the original WiFi signal measures.

Furthermore, we compared our method with various WiFi fingerprinting approaches, including RSS fingerprinting, RTT fingerprinting, mixed RSS-RTT fingerprinting, and with WiFi RTT trilateration. We observed that our proposed algorithm outperformed all other traditional WiFi indoor positioning models in all four complex indoor environments (refer to Figure 8 (a), (b), (c), and (d)), achieving superior results with positioning accuracies ranging between 0.75 m and 1.25 m in the CDF curve for all four testbeds. Although our algorithm slightly trailed RTT fingerprinting in the LOS lecture theatre testbed, it showcased superior performance in the other two testbeds (NLOS and mixed LOS-NLOS). Figure 8 demonstrates the consistent accuracy of our proposed algorithm, achieving an overall accuracy of up to 0.8 meters in 80% of the instances.

Moreover, in the building floor testbed, we conducted evaluations employing grid sizes of 1.2 × 1.2 m^2 and 1.8 × 1.8 m^2. As shown in Figure 8 (d), while the use of a 1.2 × 1.2 m^2 grid adversely affected the overall performance of the proposed algorithm, adopting a 1.8 × 1.8 m^2 grid achieved accuracy levels comparable to those of the original grid size. This is because when using a larger grid size, the fingerprints among each reference point became even more distinguishing. This demonstrates that the positioning error of our proposed algorithm is more concentrated below 1 metre level and is more robust in providing metre-level accuracy performance.

Finally, we observed that utilising statistical features for selecting the best positioning model had a positive effect only on RSS fingerprinting in the mixed LOS-NLOS office testbed. Most of the time, the statistical features extracted were equal to or even less than original preprocessed WiFi signal measures. This occurred because when extracting statistical features, the informative information hidden in separate WiFi samples was eliminated to form general statistics.

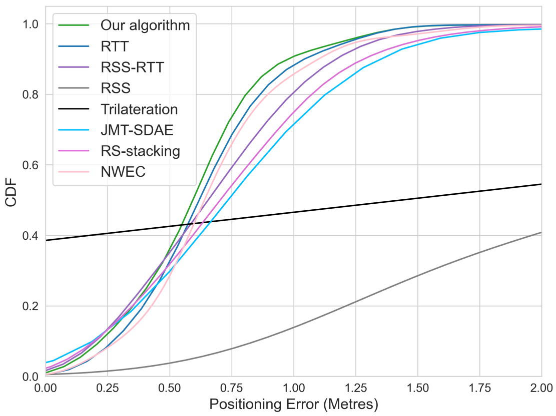


Fig. 7: Performance comparison with different popular WiFi indoor positioning models using original features. RTT, RTT-RSS and RSS indicate fingerprinting algorithms using corresponding input features. Our proposed algorithm achieved an accuracy of up to 0.8 m, 80% of the time.

VI. Conclusion

In this study, we introduced a novel algorithm that dynamically selects the most suitable positioning model for each location. To evaluate our algorithm's performance and ensure its adaptability across diverse scenarios, we conducted experiments in four real-world datasets representing complex indoor environments: a long corridor, a lecture theatre, an office room, and a whole building floor. These datasets covered various LOS/NLOS conditions. Across all 4 testbeds, RTT fingerprinting consistently outperformed other models, demonstrating superior accuracy in more than 36% of the locations using the original RSS and RTT signal measures. Surprisingly, RSS fingerprinting excelled in certain locations in the mixed LOS-NLOS scenarios. Notably, RTT trilateration failed to perform in many NLOS locations. These observations demonstrate the need for dynamic model switching. Compared to traditional WiFi fingerprinting methods and state-of-the-art ensemble methods, our algorithm achieving up to 32% accuracy improvement over stacking algorithms and a 1.8-meter RMSE reduction compared to standard RSS fingerprinting. Our algorithm consistently delivered superior performance in NLOS and mixed scenarios, achieving an overall 0.8-meters accuracy in 80% of instances.

Future research could delve into integrating Machine Vision and IMU-based positioning methods, extending the applicability of the proposed dynamic model selection algorithm. Given its flexibility regarding positioning models and input signal features, the algorithm's general concept could be extended to incorporate alternative wireless signal measures like UWB, BLE or WiFi CSI. Additionally, exploring more efficient positioning models and advanced positioning model selection classifiers is essential to enhancing prediction accuracy. This opens avenues for broader applications and advancements in wireless indoor positioning technologies.

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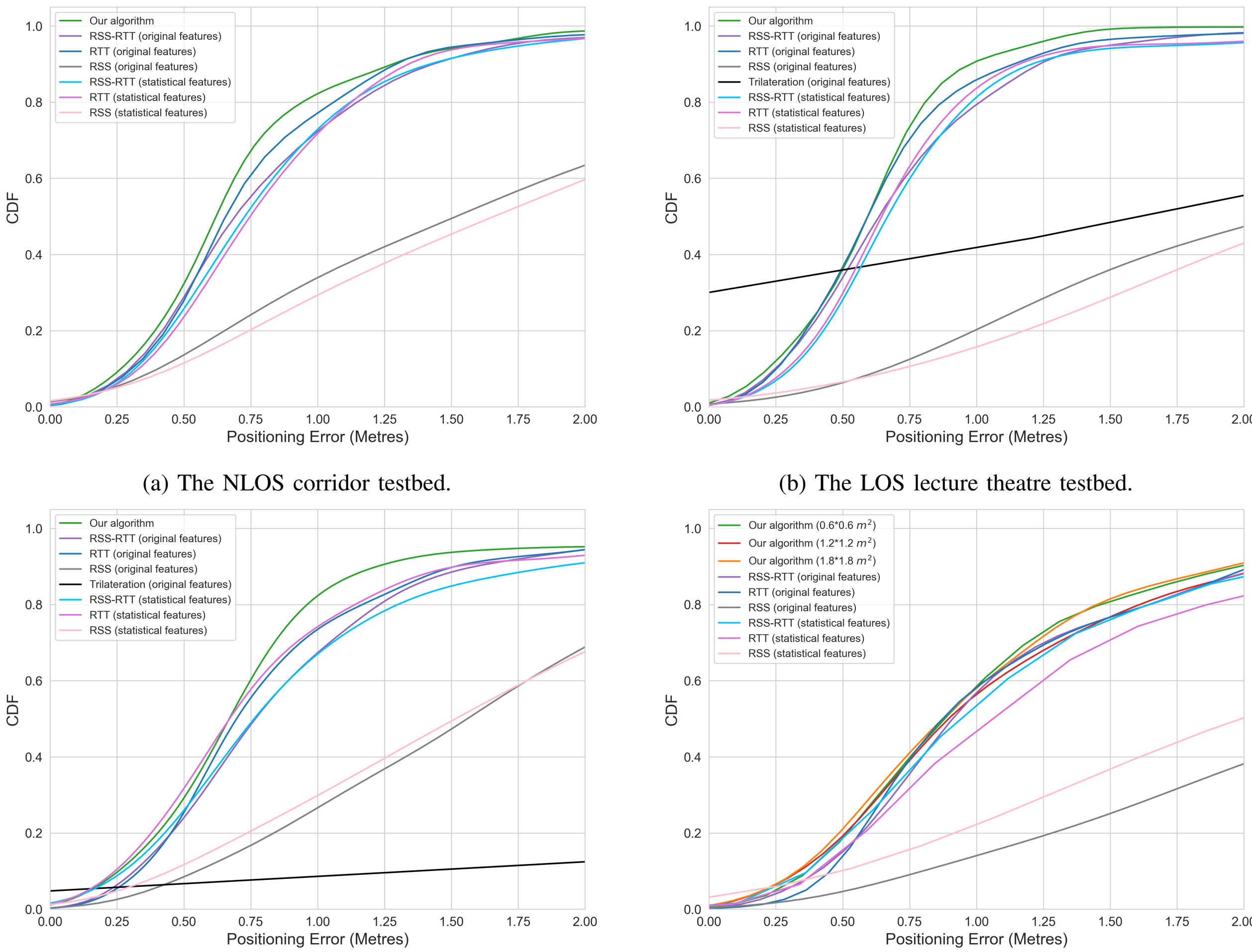

(a) The NLOS corridor testbed.

(b) The LOS lecture theatre testbed.

(c) The mixed LOS-NLOS office testbed.

(d) The mixed LOS-NLOS building testbed.

Fig. 8: Performance comparison with different popular WiFi fingerprinting models utilising different WiFi input features. Our proposed algorithm achieved a notable improvement of up to 1.8 meters in RMSE compared to popular WiFi indoor positioning models.

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Xu Feng received the B.S. degree from Zhejiang University, Hangzhou, Zhejiang, China, in 2020, and is currently pursuing his Ph.D. degree in Computer Science at Royal Holloway University of London, United Kingdom. His research focuses on Machine Learning for WiFi technologies, with applications for indoor positioning.

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Khuong An Nguyen is a Senior Lecturer of Machine Learning at Royal Holloway University of London. He hold a PhD, an MPhil (Cantab), and a BSc (Hons) at Royal Holloway University and University of Cambridge. His research focuses on Machine Learning theory and its applications in Navigation and Smart Healthcare.

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Zhiyuan Luo is a Professor of Machine Learning at Royal Holloway University of London. He hold a PhD at Heriot-Watt University. His research focuses on Machine Learning, Data Analysis, Networked Systems, Agent-based Computing, and applications of these algorithms and techniques.