A dynamic model switching algorithm for WiFi fingerprinting indoor positioning

Xu Feng
University of Brighton
Brighton BN2 4GJ, United Kingdom
X.Feng@brighton.ac.uk

Khuong An Nguyen
Royal Holloway University of London
Surrey TW20 0EX, United Kingdom
Khuong.Nguyen@rhul.ac.uk

Zhiyuan Luo
Royal Holloway University of London
Surrey TW20 0EX, United Kingdom
Zhiyuan.Luo@rhul.ac.uk

***Abstract*—In 2023, there are various WiFi technologies and algorithms for an indoor positioning system. However, each technology and algorithm comes with their own strengths and weaknesses that may not universally benefit all building locations. Therefore, we propose a novel algorithm to dynamically switch to the most optimal positioning model at any given location, by utilising a Machine Learning based weighted model selection algorithm, with WiFi RSS and RTT signal measures as the input features. We evaluated our algorithm in three real-world indoor scenarios to demonstrate an improvement of up to 1.8 metres, compared to standard WiFi fingerprinting algorithm.**

***Index Terms*—WiFi fingerprinting, model switching, feature selection.**

I. Introduction

WiFi fingerprinting has been one of the most popular methods for infrastructure-free indoor positioning, due to its ability to capture all the nuances of the WiFi signal attenuation at every location in the building. Currently, the most prevalent WiFi signal measures for indoor positioning are the Received Signal Strength (RSS), Channel State Information (CSI) and Round-Trip Time (RTT). However, each signal measure has its own strengths and weaknesses. For example, RTT measures excel when there is a clear line-of-sight, whereas RSS measures perform best overall in severely attenuated non-line-of-sight condition [1].

To this end, we propose an algorithm to switch to the most optimal indoor positioning model for each location. Our algorithm employs a novel weighted model selection technique that dynamically assigns different weights based on the signal characteristics of the location. For implementation on heterogeneous devices, especially smartphones, we specifically focus on the WiFi RSS and RTT signal measures as the input (because CSI is not yet readily available on commercial Access Points and smartphones). We implemented the most popular fingerprinting approaches, including RSS fingerprinting, RTT fingerprinting, a hybrid RSS-RTT fingerprinting, as well as RTT trilateration for comparison. For evaluation, we conducted a comprehensive comparison with three state-of-the-art Machine Learning and Deep Learning stacking algorithms, on three real-world datasets collected in different scenarios and with different WiFi conditions (i.e., LoS, NLoS and mixed LoS-NLoS).

We summarise our contributions as follows:

- We propose a novel algorithm to dynamically select and switch to the best positioning model for each location in real-time.
- We evaluate our algorithm's performance in real-world environments.
- We publicly release three indoor positioning datasets collected from different indoor scenarios containing both RSS and RTT signal measures.

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

II. Related work

To enhance the performance of indoor positioning systems, approaches combining multiple technologies were previously explored in the literature. In [2], a feature based ensemble learning method was proposed to improve the WiFi RSS based systems. A Kalman filter was used by [3] to accelerometer, gyroscope, magnetometer and WiFi RSS trilateration. UWB, GPS and magnetic, angular, gravity and gravity were fused in [4] by a weighted fusion algorithm. The system proposed by [5] used an error state extended Kalman filter to combine 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. The system in [6], [7] adopted a gradient boosting decision tree (GBDT) to make WiFi RSS fingerprinting based on crowdsourcing radio map. The authors in [8] proposed a weighted ensemble classifier based on Dempster–Shafer belief theory to enhance WiFi RSS positioning. The method proposed by [9] 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. In [10], a Tree-based localisation method was used as a secondary learner to make predictions for WiFi RSS indoor positioning. To maintain accuracy, [11] 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. The system proposed by [12] used CNN, SVM, ELM, and XGBoost as the primary learner and stacked an XGBoost as the secondary learner for WiFi fingerprinting.

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

III. PROBLEM FORMULATION

For indoor fingerprinting, the environment is divided into a total number of N reference points (RPs). A number of scans of WiFi RSS and RTT measurements is collected at each RP $P_i, (i = 1, 2, \ldots, N)$, to observe the propagation characteristics of the WiFi signals received from each AP. The fingerprinting database containing the WiFi RSS and RTT measurements from J number of APs in the environment is defined as $X = \{RSS_{i1}, RSS_{i2}, \ldots, RSS_{iJ}, RTT_{i1}, RTT_{i2}, \ldots, RTT_{iJ}\}_{i=1}^{N}$.

For preliminary indoor positioning models, the label indicating the ground truth location of each RP is defined as a vector $Y_{loc} = \{y_i\}_{i=1}^{N}$, where y_i contains the real-world coordinates of the i^{th} RP. The positioning estimation from these models is defined as $Y_{loc\_test} = \{y_{i1}, y_{i2}, \ldots, y_{iM}\}_{i=1}^{N}$, where M is the total number of preliminary indoor positioning models.

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

Given a new WiFi sample $X_{test} = \{RSS_{test1}, \ldots, RSS_{testJ}, RTT_{test1}, \ldots, RTT_{testJ}\}$, the weighted model selection algorithm removes the features with the least importance and predicts the best positioning model b_{test} for the test location. Finally, the positioning estimation is made by the selected model b_{test}.

IV. PRELIMINARY POSITIONING AND WEIGHTED MODEL SELECTION ALGORITHM

This section introduces the preliminary positioning models and explains the proposed weighted model selection algorithm.

A. System architecture

Our algorithm consists of 4 steps, as follows (see Figure 1).

- Step 1: We preprocess the raw WiFi signal data by replacing the missing WiFi RTT and RSS measurements with the default values of -200 dBm for RSS and 100 m for RTT to indicate that the corresponding AP is not visible in the current location.
- Step 2: Several popular indoor positioning models are leveraged for preliminary positioning estimation.
- Step 3: The outputs from the previous step are fed into the weighted model selection algorithm. This algorithm identifies the best possible positioning model for each training indoor location.
- Step 4: Given a new WiFi sample, our model automatically selects and switches to the best positioning model, and the final location estimation is generated.

B. Preliminary WiFi-based positioning

After preprocessing the input WiFi signal measures and replacing the missing values, four WiFi-based indoor positioning models are used to generate the preliminary position estimations. They are RSS fingerprinting, RTT fingerprinting, RSS-RTT fingerprinting and RTT trilateration.

1) RSS and RTT Fingerprinting: As one of the most popular approaches for WiFi indoor positioning, fingerprinting's principle is capturing the signal attenuation at every location in the building for future reference.

The process consists of an offline phase and an online phase. In the offline phase, the WiFi signals of all locations are collected and stored in a training database. In the online phase, when the user reports a WiFi sample at an unknown location, the system compares this sample to all training samples in the database and makes the location estimation.

We implement three popular preliminary fingerprinting models, namely RSS fingerprinting model, RTT fingerprinting model, and a hybrid RSS-RTT fingerprinting model. Due to space limit, interested readers may refer to other work that describe the underlying signal properties of each model [13]–[15].

2) RTT Trilateration: Trilateration is a geometric positioning method that locates the user based on the distances between them and at least three known WiFi APs in 2-dimesional space, as follows.

$$(x-x_1)^2 + (y-y_1)^2 = r_1^2 \tag{1}$$
$$(x-x_2)^2 + (y-y_2)^2 = r_2^2 \tag{2}$$
$$(x-x_3)^2 + (y-y_3)^2 = r_3^2 \tag{3}$$

where x and y are the location coordinates of the user, (x_1, y_1), (x_2, y_2), (x_3, y_3) are the known APs' coordinates, and r_1, r_2, r_3 are the estimated distances between the user and the APs, reported by the WiFi RTT measures.

C. Weighted model selection algorithm

The positioning estimations using the preliminary positioning models in the previous step are fed into our proposed weighted model selection algorithm to identify the best model for each RP. As shown in Figure 1 and Algorithm 1, the weighted model selection algorithm consists of weights initiation, weighted feature set generation, importance-based weights updater and best positioning model selection.

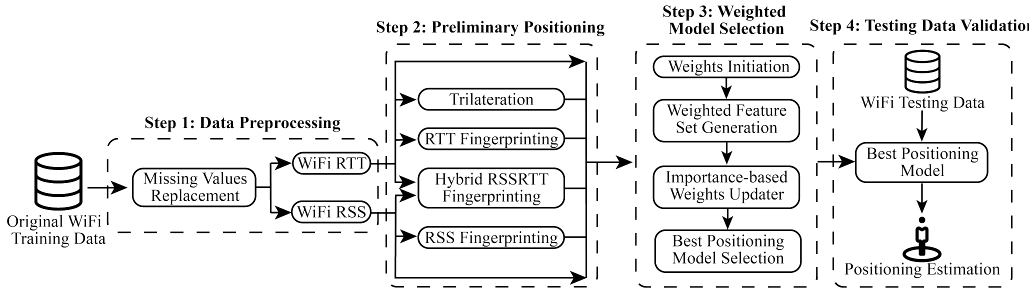

Fig. 1. Detailed step-by-step of our proposed algorithm.

Algorithm 1 Weighted Model selection algorithm.

Input: X: input WiFi RSS, RTT measure, X_{test}: testing samples Y_{loc}: ground truth coords label, $Models$: positioning models, MDI: mean decrease in impurity, PI: permutation importance, MAE: Mean Absolute Error, RFC: Random Forest Classifier.

Output: B_{best_test}: best positioning model for each testing RP

$M \leftarrow |PreliminaryPositioningModels|$
for m = 1, 2, ..., M **do**
  $model \leftarrow m^{th}$ model in $Models$
  $Y^{(m)}_{loc\_test} \leftarrow model(X, Y_{loc})$
  $E^{(m)} \leftarrow Length(Y_{loc})/(|Y^{(m)}_{loc\_test} - Y_{loc}|)$
end for
for m = 1, 2, ..., M **do**
  $w^{(m)} \leftarrow E^{(m)}/\sum_{m=1}^{M} E^{(m)}$
end for
$W \leftarrow \sum_{m=1}^{M} w^{(m)}$
$X_{weighted} \leftarrow WeightedFeature(X, Y_{loc\_test}, W)$
$B_{priori} \leftarrow argmin[MAE(\{Y^{(m)}_{loc\_test}\}_{m=1}^{M}, Y_{loc})]$
  ▷ B_{priori} contains the best model m for each RP
for m = 1, 2, ..., M **do**
  $w^{(m)}_{perm} \leftarrow PI(B_{priori}, X_{weigted})$
  $w^{(m)}_{MDI} \leftarrow MDI(B_{priori}, X_{weigted})$
  $w^{(m)} \leftarrow WeightUpdate(w^{(m)}, w^{(m)}_{perm}, w^{(m)}_{MDI})$
end for
$W \leftarrow \sum_{m=1}^{M} w^{(m)}$
$B_{best\_train} \leftarrow RFC(X_{weighted}, W)$
$B_{best\_test} \leftarrow RFC(B_{best\_train}, W)$
return B_{best_test}

When integrating the preliminary positioning results and the preprocessed WiFi signal measures into the weighted model selection algorithm, the initial weights are generated for each input feature to represent their importance in determining the user's location. In this weights initiation process, the mean absolute error (MAE) is utilised to evaluate the performance of the preliminary models from the previous step. The smaller the MAE is, the more accurate the model is. The weight $w^{(m)}$ of the m^{th} ($m \in \{1, 2, \ldots, M\}$) model is defined as:

$$w^{(m)} = \frac{E^{(m)}}{\sum_{i=1}^{M} E^{(i)}} \tag{4}$$

$$E^{(m)} = \frac{n}{|Y^{(m)}_{loc\_test} - Y_{loc}|} \tag{5}$$

where n indicates the length of the ground truth coordinates of each RP 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.

After the weights initiation process, each feature is assigned with a weight, indicating how strong its correlation to the ground truth label is. Then a new feature set, containing the preliminary positioning estimations, preprocessed WiFi RSS and RTT signal measures and their corresponding weights, is generated for the importance-based weights updater. The weighted model selection algorithm's ultimate goal is determining the best positioning model for a newly reported WiFi sample. Therefore, in the importance-based weights updater, each feature's importance in predicting the best positioning model is evaluated by Permutation Importance (PI) and Mean Decrease in Impurity (MDI), as follows.

Permutation Importance: Permutation Importance evaluates the importance of each feature by randomly shuffling each feature from the original input feature set. The idea of permutation importance is that the meaningful information of an input feature will be removed when randomly shuffled. The prediction accuracy of the classifier will decrease when a more important feature is shuffled. Thus, after a total number of R iterations of random shuffling, the mean decrease in the accuracy of each feature is calculated. In every iteration, the feature importance $w^{(m)}_{perm}$ in the m^{th} model is defined as:

$$w^{(m)}_{perm} = Acc_{orig} - Acc_{perm} \tag{6}$$

$$Acc_{orig} = model(\mathcal{X}, \mathcal{Y}) \tag{7}$$

$$Acc_{perm} = model(\mathcal{X}_{perm}, \mathcal{Y}) \tag{8}$$

where $model$ is the classifier trained for the best positioning model selection, $\mathcal{X}$ and $\mathcal{Y}$ indicate the original input feature and label to the classifier, $\mathcal{X}_{perm}$ is the randomly shuffled input feature set, and Acc_{orig} and Acc_{perm} are the accuracy of the original and shuffled input feature set. Figure 2 gives an example of the permutation importance of the input feature set to the best positioning model prediction. Only features that would increase the prediction accuracy are given higher and positive importances, and selected by the proposed algorithm. The bigger the positive importance is, the more important the feature is to the weighted model selection algorithm.

Mean Decrease in Impurity: Mean decrease in impurity evaluates the importance of the input feature by measuring how much it helps to decrease Gini impurity (GI) in decision

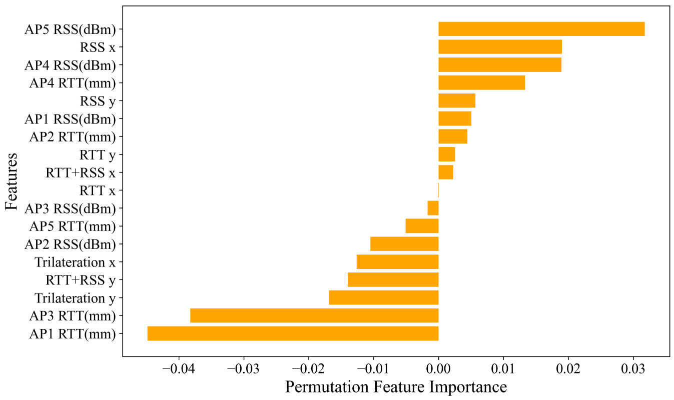

Fig. 2. The permutation importance of an input feature set used to decide the most optimal positioning model for the lecture theatre testbed. Negative importance means that the feature may decrease the positioning accuracy.

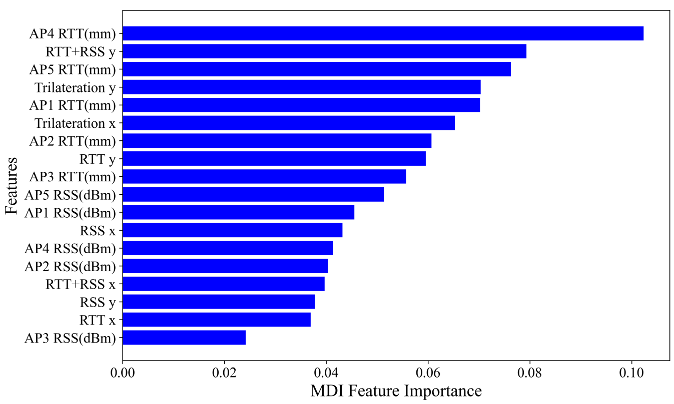

Fig. 3. The MDI importance of an input feature set used to decide the most optimal positioning model for lecture theatre testbed. Bigger value indicates a more important feature.

tree-based algorithms. GI indicates the probability of misidentification for a randomly chosen variable that is randomly labelled according to the distribution of class labels in the dataset. The mean decrease in Gini impurity (MDG) of feature j for random forest is defined as:

$$MDG_{j,i} = \sum_{k=1}^{n_i} p_{k,i} \cdot \Delta G_{k,i}(j) \tag{9}$$

$$MDG_j = \frac{1}{N_T} \sum_{i=1}^{N_T} MDGI_{j,i} \tag{10}$$

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, $\Delta G_{k,i}(j)$ is the decrease in GI caused by splitting on feature j at node k in tree i, N_T is the total number of trees in the Random Forest, MDG_j is the overall MDG of feature j 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.

In the importance-based weight updater, the permutation and MDI importance of each input feature $w_{perm}^{(m)}$ and $w_{MDI}^{(m)}$ are utilised to update the initial weight $w^{(m)}$ from the weights

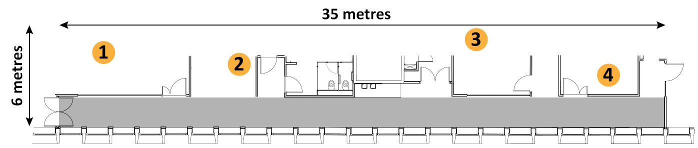

Fig. 4. The layout of the long corridor testbed. This is an entirely NLoS scenario. The orange points indicate the APs' location. All WiFi measurements were collected in the grey area.

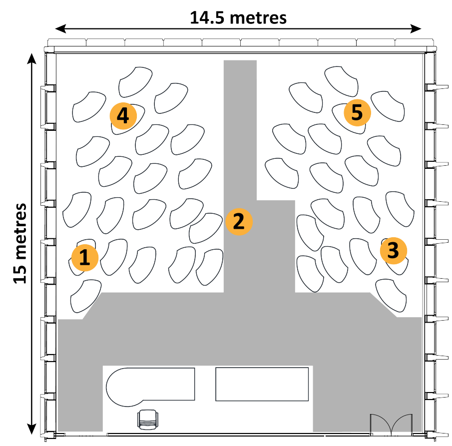

Fig. 5. The layout of the lecture theatre scenario. This is an entirely LoS scenario. The orange dots indicate the locations of the APs. All WiFi measurements were collected in the grey area.

initiation. 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. Finally, an updated feature set is selected for best model identification. Based on the final feature set decided, the weighted model selection process would select the best possible model for a new sample in the testing data validation step.

V. EXPERIMENTAL SETUP AND EMPIRICAL RESULTS

This section investigates the performance of our proposed algorithm.

A. Testbeds

To evaluate the performance of our algorithm and validate its generalisation and transferability, three datasets of complex real-world scenarios were collected in a long corridor, a lecture theatre, and an office room. The corridor testbed presents a completely NLoS scenario of more than 35 × 6 m^2, where no RP had any LoS path to the 4 APs (see Figure 4). The lecture theatre scenario was a totally LoS one of more than 15 × 14.5 m^2, where all RP had LoS path to all 5 APs in the testbed (see Figure 5). The office room consists of a 18 × 5.5 m^2 area with mixed LoS-NLoS conditions, where each RP would have at least one LoS AP (see Figure 6). All three testbeds were evenly divided into 0.6 × 0.6 m^2 grids, while making sure the training and testing RPs did not overlap.

An LG G8X ThinQ smartphone and 5 WiFi RTT-enabled Google APs were used in the experiments. The ground-

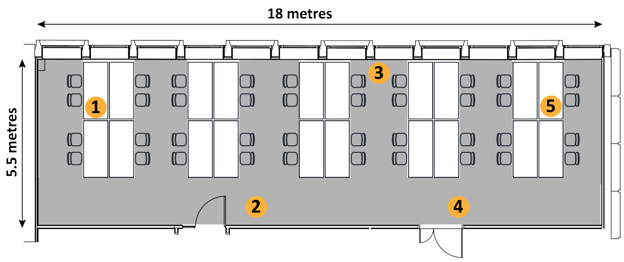

Fig. 6. The layout of the office room scenario. This is a mixed LoS-NLoS scenario, where each RP would have at least one LOS AP and some NLoS APs. The orange dots indicate the locations of the APs. All WiFi measurements were collected in the grey area.

TABLE I
SUMMARY OF OUR THREE REAL-WORLD DATASETS.

Data features	Lecture Theatre	Office	Corridor
Test bed area	15 × 14.5 m^2	18 × 5.5 m^2	35 × 6 m^2
Grid size	0.6 × 0.6 m^2	0.6 × 0.6 m^2	0.6 × 0.6 m^2
Number of RPs	120	108	114
Samples per RP	60	60	60
All samples	7,200	6,480	6,840
Training samples	5,400	4,860	5,130
Testing samples	1,800	1,620	1,710
Signal measure	RTT, RSS	RTT, RSS	RTT, RSS
WiFi condition	LoS	LoS/NLoS	NLoS

TABLE II
THE NUMBER OF RPS IN WHICH THE POSITIONING MODEL PERFORMED BEST. IT WAS INTERESTING TO OBSERVE THAT THERE WAS NO CLEAR DOMINANT MODEL FOR ALL LOCATIONS.

Positioning model	Lecture Theatre (120 RPs)	Office (108 RPs)	Corridor (114 APs)
RTT trilateration	19	1	0
RSS fingerprinting	3	16	15
RTT fingerprinting	56	55	53
RSS-RTT fingerprinting	42	36	46

truth label and the LoS condition of each RP were manually recorded and verified by two people. A summary of the three datasets is shown in Table I. They are also publicly available at https://github.com/Fx386483710/Dataset_for_Model_Selection.

B. Empirical Results

As the WiFi signal measures are attenuated by complex indoor interior, the most optimal indoor positioning models may vary from location to location. To investigate the best positioning estimator for each RP, we performed localisation for every RP in all three datasets with the four underlying models (i.e., RSS, RTT, and hybrid RSS-RTT fingerprinting and RTT trilateration). To better evaluate the positioning error, root mean square error (RMSE) was utilised in this section to measure the average difference between the positioning estimation and the ground truth coordinate. Note that the testing RPs and training RPs did not overlap. The results of the best positioning model for each RP are shown in Table II.

We observed that for all three testbeds, RTT fingerprinting performed the best overall in almost 50% of the RPs (see

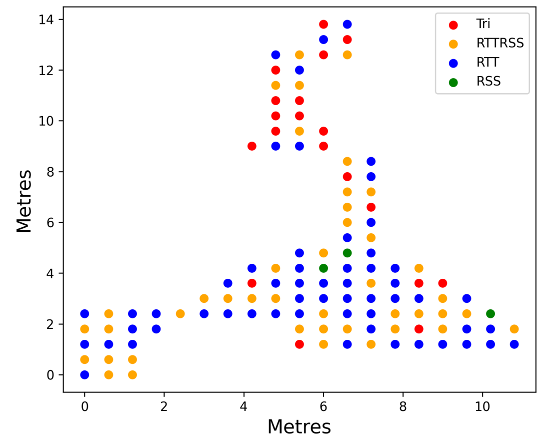

Fig. 7. The best positioning model for each RP in the lecture theatre testbed. RTT fingerprinting excelled in 56 out of 120 RPs.

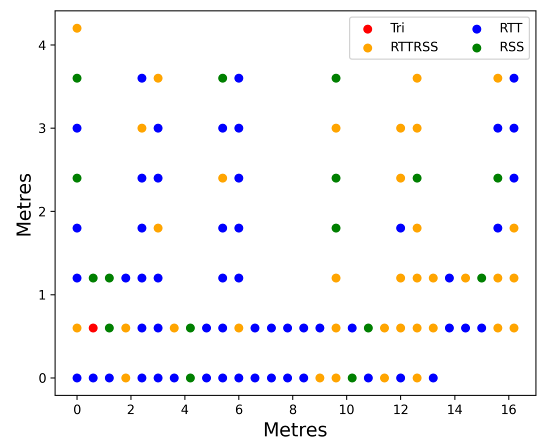

Fig. 8. The best positioning model for each RP in the office testbed. RTT fingerprinting excelled in 55 out of 108 RPs.

Figures 7, 8 and 9). Surprisingly, although widely claimed to deliver sub-metre-level accuracy, RTT trilateration struggled with most RPs even in LoS condition. Interestingly, in the mixed LoS-NLoS office and corridor testbeds, RSS fingerprinting could outperform RTT fingerprinting in certain RPs. This result strongly indicated there was no best overall positioning model for all scenarios. Thus, the overall positioning estimation could be improved by dynamically switching models.

To investigate the performance of our proposed algorithm, we compared its performance with standard WiFi fingerprinting (i.e., RSS fingerprinting, RTT fingerprinting, hybrid RSS-RTT fingerprinting and RTT trilateration) and state-of-the-art Machine Learning and Deep Learning ensemble methods JMT [9] and RS-stacking [12] (see Table III and Figure 10).

It was observed that our algorithm achieved up to 32% more accurate positioning estimation compared to the state-of-the-art stacking algorithms, and up to 1.8 metres RMSE improvement compared to standard WiFi RSS fingerprinting

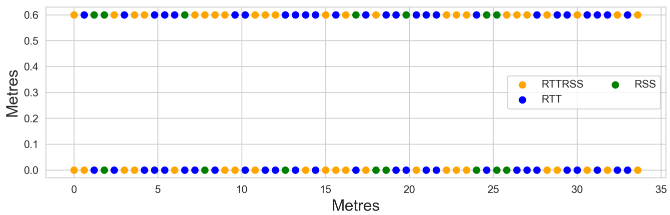

Fig. 9. The best positioning model for each RP in the corridor testbed. RTT fingerprinting excelled in 53 out of 114 RPs.

TABLE III
PERFORMANCE COMPARISON OF THE RMSE (M) OF DIFFERENT MODELS.

Model Name	Lecture Theatre	Office	Corridor
RSS-RTT fingerprinting	0.612	0.729	0.612
RTT fingerprinting	**0.559**	0.718	0.704
RSS fingerprinting	2.356	1.423	1.315
Trilateration	1.176	1.073	412.257*
RF stacking	0.640	0.851	0.755
JMT	0.716	0.857	0.705
RS-stacking	0.724	0.824	0.672
Proposed method	0.570	**0.698**	**0.569**

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

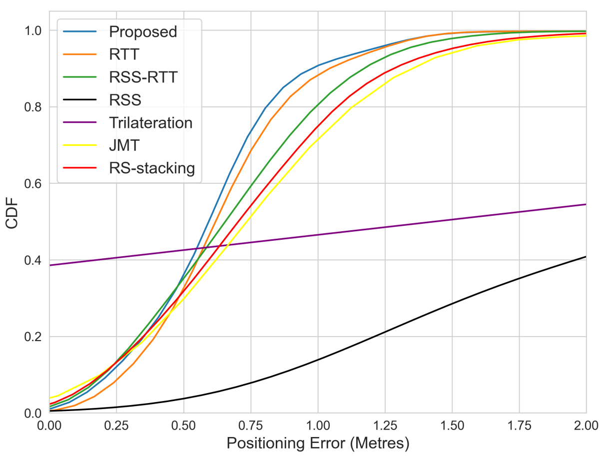

Fig. 10. CDF comparison of different WiFi indoor positioning models. Our proposed framework achieved an accuracy of up to 0.8 m, 80% of the time.

method. The stacking approaches which focus on the individual positioning model lacked the information hidden in the original WiFi signal measures that our proposed method incorporated.

Although our method's performance was slightly behind to RTT fingerprinting in the LoS lecture theatre testbed, it performed better in the other two testbeds (NLoS and mixed LoS-NLoS). As shown in Figure 10, our proposed algorithm delivered an overall accuracy of up to 0.8 m, 80% of the time.

VI. CONCLUSIONS

In this paper, we have proposed a novel algorithm to dynamically decide the most optimal positioning model for each WiFi positioning sample. For a newly reported WiFi sample, the algorithm would automatically switch to the best model and make positioning estimation. The performance of our proposed algorithm was evaluated on three real-world indoor datasets, which were also made available for further research. We demonstrate an improvement of up to 1.8 metres using RMSE, compared to standard WiFi fingerprinting and state-of-the-art stacking methods. For future work, we could include machine vision and IMU based positioning methods to further enhance the positioning performance.

REFERENCES

[1] X. Feng, K. A. Nguyen, and Z. Luo, "Wifi access points line-of-sight detection for indoor positioning using the signal round trip time," *Remote Sensing*, vol. 14, no. 23, p. 6052, 2022.

[2] A. K. Panja, S. F. Karim, S. Neogy, and C. Chowdhury, "A novel feature based ensemble learning model for indoor localization of smartphone users," *Engineering Applications of Artificial Intelligence*, vol. 107, p. 104538, 2022.

[3] A. Poulose, O. S. Eyobu, and D. S. Han, "A combined pdr and wi-fi trilateration algorithm for indoor localization," in *2019 International Conference on Artificial Intelligence in Information and Communication (ICAIIC)*. IEEE, 2019, pp. 072–077.

[4] K. Zhang, C. Shen, Q. Zhou, H. Wang, Q. Gao, and Y. Chen, "A combined gps uwb and marg locationing algorithm for indoor and outdoor mixed scenario," *Cluster computing*, vol. 22, pp. 5965–5974, 2019.

[5] C. Yang, Z. Cheng, X. Jia, L. Zhang, L. Li, and D. Zhao, "A novel deep learning approach to 5g csi/geomagnetism/vio fused indoor localization," *Sensors*, vol. 23, no. 3, p. 1311, 2023.

[6] J. Yang, X. Zhao, and Z. Li, "Crowdsourcing indoor positioning by light-weight automatic fingerprint updating via ensemble learning," *IEEE Access*, vol. 7, pp. 26 255–26 267, 2019.

[7] X. Feng, K. A. Nguyen, and Z. Luo, "A survey of deep learning approaches for wifi-based indoor positioning," *Journal of Information and Telecommunication*, vol. 6, no. 2, pp. 163–216, 2022.

[8] P. Roy, C. Chowdhury, M. Kundu, D. Ghosh, and S. Bandyopadhyay, "Novel weighted ensemble classifier for smartphone based indoor localization," *Expert Systems with Applications*, vol. 164, p. 113758, 2021.

[9] H. Zhang, B. Hu, S. Xu, B. Chen, M. Li, and B. Jiang, "Feature fusion using stacked denoising auto-encoder and gbdt for wi-fi fingerprint-based indoor positioning," *IEEE Access*, vol. 8, pp. 114 741–114 751, 2020.

[10] M. Maduranga and R. Abeysekera, "Treeloc: an ensemble learning-based approach for range based indoor localization," *International Journal of Wireless and Microwave Technologies (IJWMT)*, vol. 11, no. 5, pp. 18–25, 2021.

[11] R. Wang, Z. Li, H. Luo, F. Zhao, W. Shao, and Q. Wang, "A robust wi-fi fingerprint positioning algorithm using stacked denoising autoencoder and multi-layer perceptron," *Remote Sensing*, vol. 11, no. 11, p. 1293, 2019.

[12] G. JunLin, Z. Xin, W. HuaDeng, and Y. Lan, "Wifi fingerprint positioning method based on fusion of autoencoder and stacking mode," in *2020 International Conference on Culture-Oriented Science & Technology (ICCST)*. IEEE, 2020, pp. 356–361.

[13] K. Nguyen and Z. Luo, "Evaluation of bluetooth properties for indoor localisation," *Progress in Location-Based Services*, pp. 127–149, 2013.

[14] K. A. Nguyen, Z. Luo, G. Li, and C. Watkins, "A review of smartphones-based indoor positioning: Challenges and applications," *IET Cyber-Systems and Robotics*, vol. 3, no. 1, pp. 1–30, 2021.

[15] X. Feng, K. A. Nguyen, and Z. Luo, "An analysis of the properties and the performance of wifi rtt for indoor positioning in non-line-of-sight environments," in *17th International Conference on Location Based Services*, 2022.