Indoor Wireless Localization Using Consumer-Grade 60 GHz Equipment with Machine Learning for Intelligent Material Handling

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***Abstract*—Wireless indoor localization is critical for autonomous agents in modern and future smart warehouses. Millimeter-wave (mmWave) frequencies have been investigated for high-precision localization in recent years for indoor as well as outdoor positioning. We propose machine learning (ML) techniques over a radio map to estimate the location of an autonomous material handling agent used in warehouses. Based on our experimental results we demonstrate that a Multilayer Perceptron (MLP) based positioning achieves centimeter level accuracy with Root Mean Square Error (RMSE) of 0.84m. The proposed localization technique achieves up to 80% lower positioning error compared to state-of-the-art mmWave wireless localization techniques.**

***Index Terms*—Millimeter-wave, indoor localization, machine learning**

I. Introduction

Accurate and cost effective indoor positioning system is one of the major requirements towards automation for the next generation industrial revolution, Industry 4.0 and beyond. Smart and automated warehouses have been a key focus in the industrial development, that includes advanced communication systems, autonomous navigation and automation of machines [1]–[3]. Precise and robust localization is one of the critical requirements for the Industry 4.0 as it forms the basis to ensure the safety of the workers as well as to navigate the autonomous agents (or vehicles).

For indoor localization such as warehouses, wireless sensor based approaches are vastly investigated [4] and have been the preferred positioning approach for indoor environment due to the low cost, easy deployment and power efficiency. Many wireless based localization techniques are based on trilateration and triangulation [5], for which Line-of-Sight (LoS) measurement is required. Such techniques are not efficient for accurate indoor positioning in environments such as, warehouses due to lack of proper LoS due to obstacles, moving components and the shelf partitions. Furthermore, large number of errors occur in the triangulation technique because of the multi-route radio wave phenomenon in which different signals are reflected and cause interference. Fingerprinting based approaches [5], [7] are more suited for indoor environment and in our work we propose to use millimeter-wave (mmWave) based wireless technology for wireless fingerprinting using Machine Learning (ML). Using Global Positioning System (GPS), good outdoor accuracy can be achieved but it lacks performance in indoor environment due to weak signal strengths.

Millimeter-wave frequencies ranges between 30 GHz to 300 GHz, particularly in the unlicensed 60 GHz spectrum, allows higher data rates of multi-gigabit-per-second making it suitable for many applications that require high speed wireless data rates like robot navigation and smart cities [6]. Hence, for such applications it may well suit to utilize the mmWave communication, efficient and cost effective localization methodologies will be possible as we can reuse the already existing communication infrastructure. This will significantly reduce the overall cost. Further with the advancement in the field of the autonomous vehicles, mmWave technology is essential for providing the communication infrastructure for multi-giga-bit data rate communication requirement for these autonomous vehicles or agents [7], [8]. Our approach is to reuse this high-speed communication infrastructure to provide the localization information which is one of the fundamental requirement for any autonomous systems.

The contributions of this work are outlined as follows:

- We design an indoor warehouse localization system using consumer-grade off-the-shelf 60 GHz wireless routers. For this, we use Signal-to-Noise-Ratio (SNR) as a feature from consumer-grade wireless Access Points (APs) in ML based localization algorithm.
- We implement a ML based learning algorithm for the task of localization. We evaluate our trained ML models in a working warehouse environment to accurately test the localization accuracy.
- Further, we evaluate and study the impact of the router orientation with localization accuracy. As consumer-grade 60 GHz routers have irregular beam shapes and this changes the SNR information received with the orientation of the receiver's antenna.
- We introduce a method to deal with the missing feature

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information from the APs during the training and inference of the ML models as consumer-grade APs can lose connectivity intermittently.

II. Related Work

WiFi based wireless indoor localization has been researched in past years [9]. In [10], authors have evaluated the performance of mmWave wireless systems for localization and have shown that the same techniques that can be used for WiFi can also be used in mmWave systems. The results were simulation based and the hardware changes required to generate the necessary signals for different localization techniques were not discussed.

Authors in [11] have used off-the-shelf hardware for the 60 GHz and designed a location estimation system using the particle filter with linear programming and Fourier analysis and have reported sub meter accuracy. However, in their methodology they used 400 measurements per location during their data collection and this can be very time consuming for a large scale environment.

In [12], authors have proposed single-anchor based localization technique for mmWave systems. They have compared distance and angle based localization techniques along with fingerprint based technique. The path loss model characterization needs to be done for Received Signal Strength (RSS) based triangulation and it is usually done by experimentation. For mmWave, the path loss model parameters can vary significantly for different receiver location within the same environment. Therefore, mechanisms to estimate location which are more resilient to statistical variations in the channel model needs to be developed.

III. System Architecture

In this section, we describe the wireless features used by our system, the placement strategy of APs inside the warehouse, the data collection setup, and the feature extraction process for the proposed localization methodology.

A. AP Deployment in the Warehouse

The APs used in our system are the 60 GHz TP-Link AD7200 wireless routers [13]. We select these routers at the time of experimentation as they were the only available 60 GHz consumer-grade routers. Fig. 1 shows the placement of the APs on the ceiling of the warehouse as the top view. The APs are mounted on the warehouse ceiling along the edges of the aisle in a zig-zag arrangement depending on the availability of trusses. This particular placement of APs is used to maximize the coverage of wireless signal within the aisle. A 60 GHz router is configured in the client mode and is mounted on top of the autonomous agent. The routers are configured in the AP mode by default. Configuring the routers in client mode is done by flashing the router by the firmware provided by [11]. Also as shown in Fig. 1, the total length of an aisle used in our experimental setup is 20.11 meters (66 feet) and we have placed five APs within the aisle.

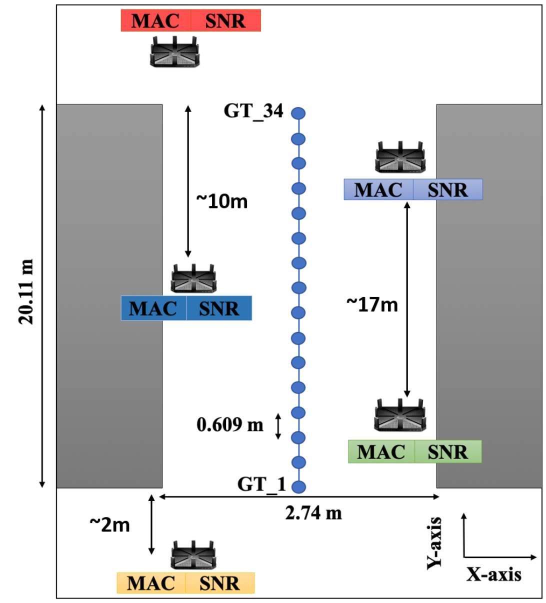

Fig. 1. Blue dots indicates the positions at which data is collected

B. Data Collection Routine

We adopt a supervised ML model for the task of localization in the warehouse as our training models are trained by using the input features along with the corresponding output labels. For supervised ML algorithms, the training data is required to build the learning model. The training data consists of the input features and the corresponding Ground Truth (GT). This is the output that the learning model uses to evaluate its prediction accuracy and then it tries to minimize the prediction error during the training process.

For different ML tasks like image classification, object detection, the training datasets are widely available online but as our task uses the new 60 GHz hardware inside a warehouse and to the best of our knowledge no prior datasets are available online. We divide the aisle into multiple coordinate location a shown in Fig. 1, where the (blue) dots within the aisle represents the location at which we collect the SNR signals from the APs at the client. Each of the locations are carefully marked using measuring tape and lasers for precise alignment form GT location 1 (GT_1) to GT location 34 (GT_34). The separation between the marked locations along the vertical y-axis is 0.609 meters (2 feet) i.e., precision of localization is less than 2 feet.

During data collection process, the SNR information is recorded 10 times at each location on the client and this is published from the agent to a remote server. At the time of experimentation, no traditional computing device (laptop) is available with 60 GHz wireless client, so, on the client router we execute in-house scripts that continuously scans for APs and get SNR values along with the Medium Access Control (MAC) address.

C. Dataset Processing Methodology

In our approach, the APs are distributed in an aisle and during the data collection routine, the client may not be able

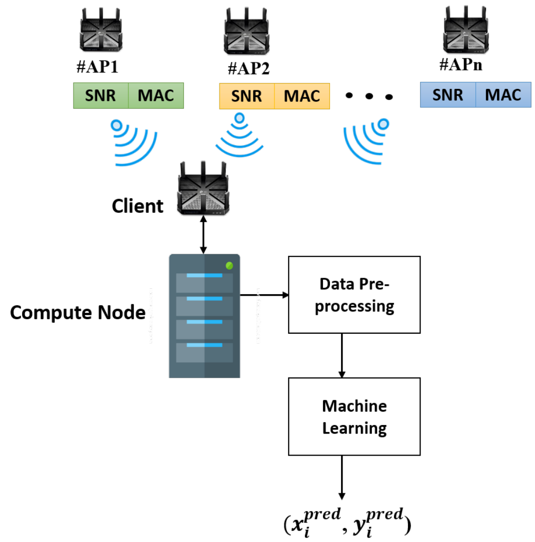

Fig. 2. Proposed 60 GHz warehouse localization system

to capture the SNR information from all available APs. This is due to the interference and the shadowing effect that can occur with the high frequency radio signals. Further, there can be situations when the SNR information from the sectors of APs are missing and this is what we also observe while analyzing the collected dataset. This missing sector information and APs (features) are inconsistent and this can cause our model to not generalize for unseen test data. To overcome the missing SNR information, which can have large impact on the performance, we perform a mean substitution of for each missing feature in the training dataset as a pre-processing step before we train the ML model. During the test-time i.e., inference, we save the pre-processed information and perform a pre-processing on the test data before we perform inference. The performance and effect of the pre-processing on the ML models in our testbed is explained in Section IV-A.

D. Proposed Localization System

After data collection, the next step is the design and training of ML localization models. Here, we present the system architecture designed for our indoor wireless localization system. The data collected at different positions in the aisle represent a feature-rich radio map. A point in this radio map gives the SNR information seen by the client from all available APs. The 60 GHz AP uses a phased array antenna in it's hardware and the communication between the AP and client happens by selection of the best sector between them through optimization based on SNR values for all the sectors. The Talon routers consists of 36 sectors [11] so in our approach instead of using the final SNR information at the client, we extract all available SNR information from all 36 sectors to construct the radio map. Fig. 2 shows the implemented system, the agent is the vehicle that we want to localize i.e. estimate the position within the warehouse. The agent consists of a computing device, referred to as computation node in the Fig. 2. The agent used in our work is a robotic platform on which we have evaluated our system performance but we envision the agent can also be a warehouse forklift for which, the proposed system can be easily adapted.

For configuring the router in AP or client mode, we utilize the modified open source firmware source code provided by [11]. There are two phases involved in the design and implementation of our localization system. The first phase is the data collection and pre-processing stage where the required data is collected for training of ML models. The next phase is the deployment of the trained model on the agent and evaluation of the inference performance. During the first phase we perform offline data collection over number of different days in the warehouse. The rationale to collect data over multiple days is to capture the temporal variations within the SNR features that can occur due to environmental changes. This is a mandatory step for any supervised ML-based networks. In the second phase, we employ ML based localization approach which is described in more details below.

E. Machine Learning based Localization Approach

Here we present the ML approach for localization implemented for the indoor warehouse localization. Our dataset consists of X number of input features, where X is the number of APs multiplied by 36 features (or sector data) per AP in the warehouse and for each training example we have a corresponding GT. Our approach is to solve the task of localization by predicting the real valued location estimate in two-dimensional space. In this approach the GT label for each training example in our dataset will be the known position location at with SNR value was recorded. Input dimension of our dataset is $N \times X$, where N are the number of training data points. The dimension of GT in the dataset are $N \times 1$, as for each training sample we have position in two-dimension space on the warehouse floor, but in our work the agent moves in one dimension so we have only considered the dimension in which the agent moves in one direction. This is realistic in many practical warehouses for autonomous forklifts where only one forklift is allowed to move in a single aisle at any given time and usually unidirectional motion is allowed [3]. However, this approach can be extended to multiple dimensions by extending the computations to the independent dimensions.

IV. Experimental Analysis

In this section, we will discuss the performance of the our implemented localization model. Inside the warehouse we have mounted 5 APs on the ceiling along the aisle to which we had access in the working warehouse [14]. For APs and client we have used TP-Link AD7200 routers. During the data collection routine, we collect 680 data points to train our ML models and then for testing i.e., real-time localization and positioning, we employ 340 data points. We pre-process the collected dataset based on the mean imputation method described in subsection III-C. Next, we will describe the performance of implemented localization model and we also present comparison with other state-of-the-art wireless localization techniques.

Collected dataset

#MAC_1			...	#MAC_n			X	Y
S_1	...	S_36	...	S_1	...	S_36		
0	...	15	...	15	...	10	X1	Y1
0	...	0	...	0	...	0	X2	Y2
...	...	...	...	...	...	...	...	...
12	...	17	...	20	...	19	Xm	Ym

Mean Imputed dataset

#MAC_1			...	#MAC_n			X	Y
S_1	...	S_36	...	S_1	...	S_36		
$Mean_1^1$	...	15	...	15	...	10	X1	Y1
$Mean_1^1$	...	$Mean_1^{36}$	...	$Mean_n^1$	...	$Mean_n^{36}$	X2	Y2
...	...	...	...	...	...	...	...	...
12	...	17	...	20	...	19	Xm	Ym

Fig. 3. Pre-processing of dataset

A. SNR Data Imputation Analysis

Here we evaluate the performance of the ML models with mean imputation technique as described in section III-C. We show that with our approach of feature based mean imputation of SNR signal values we achieve significant performance improvement during the training and test time inference of the ML models. Fig. 3 shows an example of mean data imputation on the training dataset before and after the imputation. In our approach we calculate the mean of each input feature, that is, each column in the input of training dataset. Then we use the computed mean to impute the missing feature corresponding to each input feature. In our training dataset, each of the sector from all APs corresponds to input feature as shown in Fig. 3.

We compare performance of our imputation technique with the single mean imputation technique which is commonly used for missing features, where the missing data is imputed by zero value. It can be seen from Table I, that compared to a zero imputation of missing data we achieve better performance improvement for all different ML models. Also for our optimized MLP we achieve 54% improvement in performance with our mean imputation technique. This behavior is observed due to the fact that for high frequency wireless signals, particularly in the range of mmWave, there exists high temporal variations. This temporal variation is also dependent on the environment and our environment is a complex working warehouse, where due to the metallic structures, shelf content and shelf partitioning the client may drop SNR.

B. Localization Performance Analysis

For ML based localization we have trained and evaluated three different regression based ML models namely, Linear Regression (LR), Support Vector Regression (SVR) and MLP. Table II illustrates the performance comparison between the three different ML models. It can be seen that the LR model has poor performance with RMSE of 2.4m. This shows that the learning of SNR information with distances is a complex problem and needs more complex ML models. SVR and MLP performs better than LR model with improved RMSE error. But compared to SVR, the MLP model performs the best to learn the features and achieves the lowest RMSE of 0.84m which is less than 1 meter and is a desired performance for the warehouse level localization systems.

TABLE I
PERFORMANCE COMPARISON WITH AND WITHOUT IMPUTATION

ML Model	Without Imputation	With Imputation
MLP	1.86m	0.84m
SVR	3.46m	2.1m
LR	10.95m	2.4m

TABLE II
PERFORMANCE COMPARISON WITH DIFFERENT ML MODELS

ML Model	Configuration	RMSE
LR	Linear Model	2.4m
SVR	Polynomial kernel	2.1m
MLP	**200, 200, 200**	**0.84m**

Our optimized configuration of MLP consists of three hidden layers with 200 hidden neurons in each layer. At the output we have one neuron that predicts the location in y-dimension. We have used rectified linear units (ReLu) activation function at each layer and Adam optimizer during the training process. ReLu is selected as the choice for activation function, as ReLu speeds up the training process of neural networks [15] due to its lower computational complexity. We train on two datasets collected separately on two different days capturing the temporal variations in an active warehouse aisle and then test the trained model on a different separately held out dataset from a third day to investigate the efficiency of the localization in presence of temporal variations in the environment. This helps in determining the efficacy and efficiency of proposed technique in real-world scenarios where the temporal variations often happens.

Table III shows the accuracy obtained by tuning parameters and hyperparameters for a given configuration of number of hidden layer and neurons to achieve best optimized ML model. We evaluated the configurations of different MLP using three error metrics, Mean Absolute Error (MAE), Mean Square Error (MSE) and Root Mean Square Error (RMSE). For our optimized model we achieve best error accuracy in all the three metrics with RMSE of 0.84m and mean error of 0.37m. Further, we also observe that the accuracy decreases when the network becomes any deeper. This is due to the fact that for the given dataset if we make MLP more deeper with more hidden layer and neurons, the total parameters that network need to learn increases substantially and leading to overfitting and similarly underfitting for the smaller MLPs. This can be

TABLE III
ML MODEL OPTIMIZATION

Configuration	MAE (m)	MSE (m^2)	RMSE (m)
125, 125	0.61	0.88	0.94
125, 125, 125	0.81	1.14	1.07
300, 300, 300	0.47	0.9	0.95
200, 200, 200	**0.37**	**0.7**	**0.84**
200, 200, 200, 200	1.34	3.97	1.99

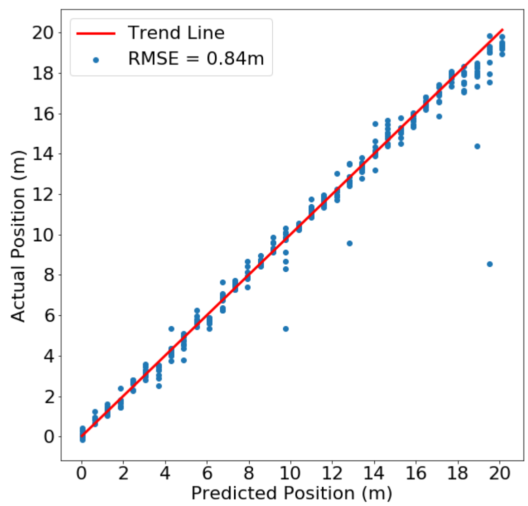

Fig. 4. Scatter plot for actual position vs predicted position

observed with the decrease in the accuracy with four hidden layers configuration shown in Table III.

In Fig. 4, we depict the scatter plot between the actual position and the predicted position from the ML model. The plot shows the correlation between the actual and the predicted location on the test data. It can be seen that the data follows a linear straight line fit representing high accuracy of the proposed indoor positioning. In [11] regression-based localization with 60 GHz APs are proposed and evaluated with a particle filter approach combined with linear programming and Fourier analysis. The median errors are reported in [11] vary between 1.1m to 1.4m. In comparison, we achieve median error of 0.22m i.e., 80% reduction, and that can be seen from the Cumulative Distribution Function (CDF) plot of our localization error in Fig. 5. It also shows that for 90% of the test cases, we achieve error less than 1 meter.

C. Antenna Orientation Analysis

In this section, we evaluate the localization performance of the agent with different antenna orientation of the client. Fig. 6 shows the radio signal map recorded by the client router for two different orientations. The figure shows the SNR values seen by the client at different positions. The red color

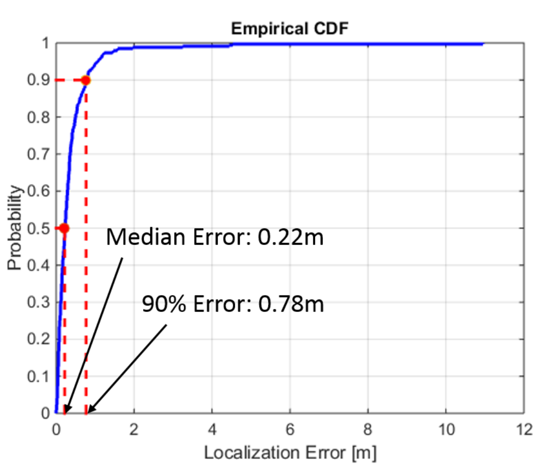

Fig. 5. CDF plot for the optimized regression model

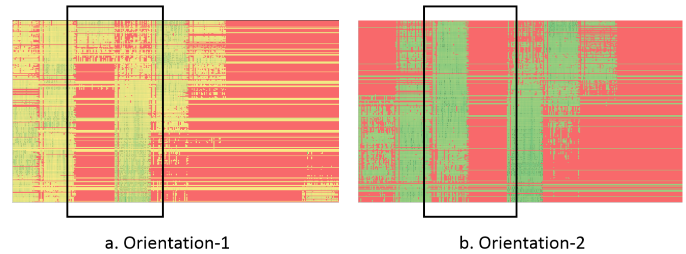

Fig. 6. Radio map of warehouse for two different orientations

indicates no SNR received. The yellow and the green region represents the non-zero SNR values received at the client. In first orientation, orientation-1, the antennas of the client router faces the ceiling upwards and in the second orientation, orientation-2, the client antenna face the shelf within the aisle. Also, different orientation effect of the APs on the ceiling can be evaluated, but the APs are a fixed infrastructure and are also used for communication so the preferred orientation of APs are selected and kept fixed.

Fig. 6a, shows the radio map for orientation-1 and Fig. 6b shows the radio map for orientation-2. The radio map represents the SNR signal values from all sectors of the APs as seen by the client router during the data collection phase. In Fig. 6 the black box region in both the radio maps shows the difference in the SNR intensity values at same locations representing the variation of the SNR with antenna orientation. This shows that the antenna orientation of the consumer-grade 60 GHz routers will affects the SNR between the client and the APs. So, for ML models to achieve maximum accuracy in localization it's critical to study the impact of the antenna orientation of the client. For this we evaluate and analyze ML models with datasets from both the orientations.

Table IV illustrates the performance comparison between the orientation and localization accuracy with three different ML models. Support Vector Regression (SVR), Linear Regression (LR) and Multilayer Perceptron (MLP) are used to evaluate the effect of orientation on localization accuracy. It can be seen for all the three ML models the orientation-1 outperforms the orientation-2 based localization approach. The ML models are optimized for the high accuracy, and for the optimized MLP we achieve high accuracy in terms of Root Mean Square Error (RMSE) for both orientations. But for orientation-1 of the client router RMSE is lowest of all three ML models. This is observed as the input feature information is captured more consistently with fewer missing sector data at the client for orientation-1. So, the ML model trained on orientation-1 is able to learn the feature information required for high localization accuracy. Hence, in our implemented

TABLE IV
LOCALIZATION PERFORMANCE FOR TWO ANTENNA ORIENTATIONS

ML Model	Orientation-1	Orientation-2
LR	2.4m	3.42m
MLP	0.84m	2.02m
SVR	2.14m	3.09m

TABLE V
PERFORMANCE COMPARISON WITH DIFFERENT WIRELESS BASED LOCALIZATION TECHNIQUES

Work	Wireless	Frequency	Environment	Methodology	Performance
Bahl [16]	RF-based	2.4 GHz	Indoor	KNN	2m-3m
Laoudias [17]	WiFi	2.4 GHz	Indoor	ANN	Mean error of 3.4m
Yang [18]	WiFi	2.4 GHz	Indoor	WiFi Fingerprinting	Mean error of 5.88m
Kanhere [19]	mmWave	28 GHz	Indoor	Fusion of AoA and received power	Mean error of 1.86m
Kanhere [19]	mmWave	28 GHz	Outdoor	Fusion of AoA and received power	Mean error of 34m
Bielsa [11]	mmWave	60 GHz	Indoor	Particle filter	Median error of 1.1m to 1.4m
Wei [20]	mmWave	60 GHz	Outdoor	DoA based WKNN fingerprint	Mean error 1.32m
Proposed Approach	**mmWave**	**60 GHz**	**Indoor**	**MLP-Regression**	**Mean error of 0.37m**

localization model we have selected orientation-1 to be the antenna orientation of the 60 GHz client router.

D. Comparison with Different Localization Approaches

In this subsection, we evaluate the performance of our localization system with different localization methodologies. Table V illustrates the performance of our approach with other wireless based localization approaches. It is seen that our ML model for 60 GHz based localization work achieves better performance in terms of localization error, with mean error of 0.37m compared to different wireless localization techniques. Further, it is seen form Table V that the mmWave based localization techniques achieves better performance compared to low frequency based WiFi techniques. This is because of the shorter wavelength of the 60 GHz band enables a higher resolution of the radio-map with richer features. Our 60 GHz based ML models outperforms the recent mmWave based localization systems proposed in [11], [19], [20] as our system uses mean imputation as pre-processing before we train the ML models and we also show that compared to simple KNN [16] and LR based models, more complex ML models like MLPs are more efficient in learning the complex SNR features.

V. CONCLUSION

We propose to use consumer-grade based 60 GHz routers for indoor wireless localization. Our approach uses machine learning to learn the wireless SNR features from the 60 GHz routers for the location estimation. In our methodology, to minimize the real-world challenges such as missing signal information from APs, we present a mean imputation approach during the training and is seen to achieve significant performance improvement during inference i.e., localization during runtime. We further analyse the effect of client's antenna orientation with respect to the APs, as for consumer-grade 60 GHz routers the signal strength depends on the antenna orientation and which affects the localization accuracy. Our localization system achieves centimeter level accuracy with RMSE of 0.84m and MAE of 0.37m which is a desired accuracy for warehouses. Our work also performs better than current WiFi and 60 GHz based localization systems with maximum improvement in accuracy by 80% compared to other consumer-grade mmWave based localization system.

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