Deep Learning Based Vehicle Localization Using Angular Characteristics of Millimeter Wave

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***Abstract*— Accurate vehicle localization is essential for connected and automated Vehicles (CAVs). However, there are significant deficiencies in the performance of Machine Learning-based localization techniques that utilize received signal strength (RSS) from millimeter-wave (mm-Wave) communications, primarily due to instability in dynamic scenarios such as those involving vehicles. In this work, we propose a vehicle localization method based on deep neural networks (DNNs) with mm-Wave propagation characteristics, including RSS and angular characteristics. Specifically, three types of artificial neural networks (ANNs), namely feed-forward, function fitting, and cascade-forward, are developed. A commercial ray tracing simulation is utilized to construct a real vehicle-to-infrastructure (V2I) communication scenario and model mm-Wave propagation characteristics. The performance of the proposed method is evaluated by testing the accuracy of the proposed ANN using different datasets. Moreover, the accuracy of the proposed method is tested by using a corrupted dataset to study its robustness against characteristics uncertainties. The numerical results show that the feed-forward model outperforms the other NN models. The constructed empirical cumulative distribution function (CDF) demonstrates that 90% of vehicles have a localization error of below 2.5m. However, the results of the corrupted dataset indicate that the accuracy degraded significantly. This aspect will be further investigated and addressed in future work.**

Keywords—vehicle localization, V2I, deep learning, mm-Wave, angular characteristics

I. Introduction

Accurate vehicle localization become crucial for intelligent transportation system (ITS), particularly with the advent of new autonomous vehicle (AV) technology [1]. In this field, achieving less than one meter of horizontal localization error is imperative. However, as mentioned in [2] and [3], the common outdoor localization systems (Global Navigation Satellite Systems such as GPS) still have limitations to satisfy these requirements especially in urban environments due to the GPS signal blockages. Therefore, some of the current research suggests that, utilizing wireless networks for vehicular localization represents the most promising alternative solution to fulfill the required localization accuracy criteria [4].

However, several techniques have been proposed for vehicle localization by utilizing the characteristics of propagated signals of wireless networks [5][6][7]. It can be categorized into range-based techniques and free-range techniques. The former techniques utilize the characteristics of the propagated signal of single or multiple references to estimate the location of the vehicle based on geometrical relationships [8][9][10][11]. These techniques have a good performance when the vehicle located in LOS to the reference; however, its performance degraded significantly when the vehicle is hidden (i.e., in NLOS condition) [12]. Furthermore, more complexity has been observed in these techniques [3]. In contrast, the later techniques, i.e., free ranging, have capability to handle the NLOS localization. Among the free ranging techniques is fingerprinting method. It is considered the most promising localization method due to its simplicity and there is no synchronization required [13].

Recently, machine learning based localization methods have been widely applied [6][14]. The localization methods based on machine learning has same fingerprinting method concept. It consists of two phases. The first phase called offline phase, where the features of the mm-wave at a relevant position are recorded and stored and later used to train the machine learning model. These data are obtained either measurement or using ray tracing simulators [15]. The second phase called online phase, where the position of the vehicle is estimated by using the trained model based on the measured features.

The trend of the recent wireless networks is to use the mm-Wave bands to satisfy the demand of transfer a large amount of data and achieve an efficient vehicular communication [16]. This motivated the researchers to utilize the characteristics of mm-Wave signal in conjunction with machine learning for localization [5][6][7]. The researchers proposed machine learning based localization methods using various features that are extracted from the characteristics of mm-wave propagation. Received signal strength (RSS) has been widely used as a training feature to train the machine learning model to estimate the relative location of the users [17][18]. However, the performance of these models is significantly dropped when the devices to be localized are located in NLOS especially in multipath environment, where the value of RSS is strongly fluctuated at these environments. However, since the angle of arrival (AOA) and time of arrival (TOA) can be precisely estimated when mm-Wave frequencies are used thanks to multiple input multiple output (MIMO) systems, some of researchers utilized these characteristics jointly with the RSS as training features to improve the performance of ML model [19][20][21]. Furthermore, the channel state information (CSI) is utilized in some research [22].

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Unfortunately, the performance of these models is still limited to reach the accuracy requirements especially when the uncertainty (noisy data) is considered.

To the best of the authors knowledge, the azimuth and elevation angel of arrival of the received mm wave signal are still not adopted jointly with the RSS as training feature in the previous works to estimate the vehicle location in urban environments. Therefore, in this work, a fingerprinting based on deep neural network (DNN) is proposed to estimate the vehicle location in urban environment. We utilize the fingertips of the received mm-wave signal for training the DNN in order to improve the localization accuracy and tackle the uncertainty of the recoded data as well. The signal has been transmitted from a single base station (SBS). The fingertips including RSS, elevation and azimuth angle of arrival of the first five received paths.

The contributions of this work are summarized in the following points:

- We proposed a DNN model using angular characteristics (azimuth and elevation) jointly with RSS to overcome the fragility of the RSS and improve the accuracy of vehicle localization in urban environments.
- We evaluated the performance of the proposed method by testing the developed DNN using different dataset. The performance of the proposed method is visualized using cumulative distribution function (CDF) for comparison purposes with the previous works.
- Contrary to the previous works, we studied and investigated the impact of uncertainties on the accuracy of the proposed method. We tested the developed DNN by using corrupted dataset in order to address the ability of the proposed method to handle the features uncertainties.

The remaining of this paper is organized as follows: Section 2 presents a review of the recent research on vehicle localization using machine learning. The system configuration and simulation setup are presented in Section 3. Section 4 describes the proposed DNN based fingerprinting. The result of evaluating the performance of the proposed method is discussed and compared with the previous work in Section 5. Finally, the conclusion and recommendations are drawn in Section 6.

II. Literature Review

Estimate the location of user devices using machine learning have been proposed in several research. As mentioned above, the characteristics of the mm-wave, such as RSS, AOA, and TOA, are the most popular utilized separately or jointly as training features in that research. In this section, we are going to present a brief review of the recent works that have been utilized a fingerprint of the information of the mm-wave channel to predict the location of the user based on machine learning.

The authors in [17] utilized the RSS of 28GHz band that received from multiple BSs to train the proposed DNN based on LSTM to estimate the users' location. Furthermore, they investigated the effect of spatial correlation in the RSS on the accuracy of localization. They proved that increasing the number of BSs may compensated the uncertainty of the RSS. In the same manner, the authors in [18] proposed a DNN model to predict the location of the user in urban environment. The beams ID combined with RSS of the arrived signal from the serve BS and neighborhood BSs are used as feature vector. The reported mean error of the proposed model was approximately 2m. however, using multiple BSs is costly and not practically. In [19], new architecture of the DNN model namely multi-feature fusion network (MFFN) is proposed. The geometric parameters of the mm-Wave channel, such as AOD, AOA, and TOA, jointly with complex impulse response (CIR) (i.e., RSS and phase), collected from a single BS, are represented as features vector. In that method, the maximum error was 2.60m. The authors in [20] proposed a DNN model to estimate the users' locations in LOS and NLOS scenarios. They utilize the characteristics, i.e., RSS, TOA, and AOA, of three multipath components to feed the proposed model. Only one BS have been considered in this work. The characteristics were generated by using the ray tracing simulator. The CNN model is proposed in [22] to estimate the location of the users. Similar to [20], they considered only one BS but they don't separate the LOS and NLOS. The channel state information (CSI) was used to feed the proposed CNN. For seeking of generalization, the testing data to evaluate the performance of the proposed model were collected at different location of training data.

In summary, up on reviewing the related works, we have observed that the azimuth and elevation angular information of the mm-wave channel jointly with RSS still have not adopted as features vector to feed the DNN. Furthermore, the uncertainties of the testing dataset, that have been considered in the RSS in [17], is generated based on normal distribution.

III. Simulation Environment Setup

In this section, the considered scenario of this work is described. Wireless InSite (WI) software, developed by Remcom, is utilized to construct a realistic V2I communication scenario in urban environment. Kuala Lumpur City Centre (KLCC), Ampang Street is selected as the area of interest of this work. First, a 3D geometrical layout of the selected area is created according to the detailed information on the reference [23] by using the using SketchUp application software. Then, the created 3D model is imported to WI as shown in Fig. 1 (a). The values of electromagnetic (EM) parameters of building, leaves, and objects were set based on [24] [25]. After that, the V2I scenario is established in the area of interest. The specification details of the constructed V2I are inspired from [26] and [27]. The EM parameters of the simulation setup and V2I specifications are listed in Table 1. The ray tracing technique is adopted to model the propagation characteristics of mm-Wave signal.

In this work, the training data is going to be collected with different sittings comparing to the test dataset as explaining in the following. First, in order to generate the training dataset, a grid of receivers is constructed to cover the considered section of Ampang Street, as shown in Fig. 1 (b). The receivers in the grid are divided into two parts, one part of the receivers is in LOS (zone 1) with the BS, while the second part is in NLOS (zone 2) with the BS. Therefore, two types of train dataset will be generated. The separated distance between all the receivers in the grid is set to 1m. The number of the received beams

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(a) (b)

Fig. 1. Wireless InSite ray tracer: (a) 3D Geometric Structure of KLCC and (b) Area of Interest (Ampang Street).

(Paths) are set to 5. The RSS, EAOA, and AAOA (i.e., 3 characteristics) of each received path will be recorded. Thus, 15 (3x5) features will be generated for the train dataset. In regard to the test dataset, a trajectory is created with 1m resolution at the same area. The dataset is collected at points on this trajectory. Some of these points are in LOS with the BS, and some of them are in NLOS. The dataset of the LOS points will be used for testing the model that will be trained by using the generated dataset from zone 1, whereas the dataset of the NLOS point will be used for testing the DNN model that will be trained by using the generated dataset form zone 2. However, during the simulation running, the vehicle moves throughout the created trajectory and capture the channel information including RSS, EAOA, and AAOA of the 5 received paths.

However, in this work, the simulation is conducted at static environment. Therefore, the uncertainties that can be occurred by the mobility of obstacles are not involved in this work; it will be considered in the future works.

IV. DNN Based Localization Method

Basically, the localization problems are regarded a complex and non-ideal problem. Thus, ML is considered the easiest and most useful methods to handle it. In this section,

Table 1. PARAMETERS OF SIMULATION SETUP

EM of Material properties			
	Material	ε_r	*σ[S/m]*
Electro Magnetic Parameters	Buildings (Concrete)	5.31	0.8967
	Vegetation-Leaf	26	0.39
	Vegetation-Branch	20	0.39
	Vehicle (Metal)	1.00	10e7
V2I Settings			
Antenna	Type	Omnidirectional	
	Polarization	Vertical	
	Gain	27 dBi	
	Height	BS = 10 m Vehicle = 2 m	
Parameters	Transmitted Power	32.0 dBm	
	Frequency	28 GHz	
	Ray tracing Technique	SBR	
	Model	Full 3D	

the architecture of the considered DNN to estimate the vehicle position will be described in terms of the type of DNN, the hyperparameters and performance evaluation. However, in this work, the most three types of DNN, which are more efficient for regression tasks, are considered to be design and trained. These types are feedforward DNN, function fitting DNN, and cascade-forward. The goal of training the DNN model is to minimize the loss function. However, since in this work, we are concerned with regression problem; therefore, the mean square error will be considered as the loss function. The vehicle's location is predicted through a learning-based optimization problem, as demonstrated in (1). The objective of the optimization problem is to learn of the mapping function X, with the aim of minimizing the Mean Squared Error (MSE) between the estimated and the actual location.

$$min\ ||\ X\ (features)\ -\ (actual\ location)\ || \tag{1}$$

MATLAB software application is used to design and train the proposed DNN. The training dataset, as described in the previous section, is labelled with the relevant information of the position and then normalized before being fed into the proposed DNN model. The training dataset consists of 15 features, as explained earlier. Meanwhile the coordinates x and y of the vehicle's location are considered as the target (output). However, we utilize the Bayesian optimization technique to tune the hyperparameters, such as number of neurons in the layer, learning rate, transfer function.

In order to evaluate the performance of the proposed DNN model, two metrics, namely the mean error $(\overline{E})$ and mean absolute error (MAE) are applied to calculate localization error based on the Euclidean distance (d_i) between the actual location (x_i, y_i) and the predicted location, $(\hat{x}_i, \hat{y}_i)$ of the vehicle. The metrics are expressed as follows

$$\overline{E}=\frac{1}{n}\sum_{i=1}^{n}|d_i| \tag{2}$$

$$\mathrm{MAE}=\frac{1}{n}\sum_{i=1}^{n}\left(|x_i-\hat{x}_i|+|y_i-\hat{y}_i|\right) \tag{3}$$

$$d_i=\sqrt{(x_i-\hat{x}_i)^2+(y_i-\hat{y}_i)^2} \tag{4}$$

To further evaluate the ability of the proposed method to defeats the uncertainties in the features of dataset, the DNN will be tested by using a corrupted dataset. The corrupted dataset is generated by adding noise to the original dataset with zero mean and random standard deviation.

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V. Results and Discussion

This section presents the discussion of the obtained results in two parts. The first part presents analysis of the generated training dataset. Meanwhile the second part discusses the results of evaluating the performance of the proposed DNN.

A. Dataset Analysis

The purpose of the data analysis is to understand the distribution of the data, identify any outliers, and study the potential of utilizing the RSS jointly with EAOA and AAOA to improve the performance of the proposed method. This will provide guidance in selecting the perfect approach for data preparation prior to feeding it into the DNN model. In this work, two of the training datasets are generated. The first one is for LOS scenario, and the second one is for NLOS scenario. However, two methods of data analysis are presented in this section. First, a normal analysis is presented by using median absolute deviation (MAD) to verify the outliers of the dataset features as shown. Second, statistical analysis based on the correlation coefficient is presented in order to investigate the relationship between the RSS and the other features, i.e., EAOA and AAOA.

The MAD values are listed in Table 2. In general, for both LOS and NLOS scenarios, most of the features have outliers; and the values of outliers increase monotonically from first received path to the fifth received path. Means that increasing the number of received paths can potentially affect the performance of the model and skew the model's predictions and lead to overfitting. Therefore, we considered the features of only the five arrived paths as features of the training dataset. However, another important observation from the table is the outliers of the RSS for NLOS scenario is higher than the EAOA. This support that, using of EAOA jointly with RSS can overcome the fragility of using RSS fingertips for NLOS scenario.

To visualize the relationship between the RSS and the other features, the correlation coefficient heatmap is created. In general, the highest correlation coefficients were exhibited in the first and the second received paths. Fig. 2 shows the correlation coefficient heatmap of the features of the first and the second received paths for LOS and NLOS scenarios. It is clear that, for LOS scenario, the absolute correlation coefficient between the RSS and EAOA of the first received paths are 0.7691 and 0.719 respectively. Means that there is a strong relationship between the RSS and EAOA. Meanwhile, a moderate relationship is shown between the RSS and AAOA. As for the NLOS scenario, the absolute correlation coefficient between the RSS and EAOA shows there is a strong relationship between RSS and EAOA of the first received path. Meanwhile a weak relationship is exhibited between RSS and EAOA of the second received path. A very weak relationship is exhibited between RSS and AAOA for the first and the second received paths. Basically, the EAOA is relevant to the propagation path length and the antenna height; meanwhile, the AAOA is relevant to surrounding areas. Therefore, the correlation coefficient between the RSS and EAOA is higher than the coefficient between RSS and AAOA.

TABLE 2. OUTLIERS OF THE DATASET FEATURES

LOS					
Feature	***Path 1***	***Path 2***	***Path 3***	***Path 4***	***Path 5***
RSS	1.0232	1.5076	2.4828	2.5152	3.0081
EAOA	1.6253	2.1888	4.1942	2.8884	5.8556
AAOA	6.3781	8.9414	34.7067	26.1007	50.0497
NLOS					
Feature	***Path 1***	***Path 2***	***Path 3***	***Path 4***	***Path 5***
RSS	3.0256	5.4246	5.2165	6.2437	8.8286
EAOA	0.4703	2.1747	0.9797	1.3824	0.7844
AAOA	2.6745	3.6035	5.4574	11.6050	36.6592

B. DNN for Vehicle Localization

As mentioned above, three types of DNN, namely feedforward DNN, function fitting DNN, and cascade-forward DNN, have been developed for predicting the vehicle's location. MATLAB software has been utilized for implementing the proposed DNNs. All the three developed DNNs have same tuned hyper-parameters. The tuned hyper-parameters of the developed DNNs are listed in Table 3. Bayesian Optimization method has been used to optimize the parameters of proposed DNNs.

For the purposes of evaluating the performance of the proposed DNNs at LOS and NLOS scenarios, a total of 800 samples of the test dataset have been collected at the selected points on created the trajectory. 622 samples of them were in LOS locations with the BS, whereas 288 samples were in NLOS locations with the BS. However, the developed DNNs have been tested by using DT_0 in order to evaluate the performance of the proposed method. A comparison of localization error of the developed DNNs is depicted in Table 4. It is clear that the feedforward DNN achieved the best performance of the localization. The maximum localization errors of feedforward were 0.0031m and 18.9797m for LOS and NLOS scenarios respectively. Meanwhile, the mean localization errors for the LOS and NLOS scenario were 0.005657m and 0.9517m respectively. The localization errors of the proposed DNNs are further visualized by using CDF as shown in Fig. 3 (a) and (b). The CDF of the proposed feedforward DNN showed that 90% of the LOS testing locations having localization error less than 0.0001m; meanwhile, 90% of the NLOS testing locations having localization error less than 1.5m. It outperformed the performance of the proposed method in [26].

TABLE 3. HYPERPARAMETERS OF THE DEVELOPED DNNS

Hyper-parameter	***Details***
Number of hidden layers	3 hidden layers
Number of Nodes	[20 30 40]
Activation Functions	{'tansig', 'tansig', 'tansig', 'purelin'}
Learning rate	0.005
Epochs size	350

TABLE 4. COMPARISON OF EVALUATION OF THE PROPOSED DNNS

Metrics (m)	**Feedforward DNN**		**Function fitting DNN**		**Cascade forward**	
	LOS	***NLOS***	***LOS***	***NLOS***	***LOS***	***NLOS***
Max. Error	0.0031	18.98	0.0057	25.37	0.0162	37.44
Mean ($\bar{E}$)	0.0056	0.952	0.0064	1.086	0.0095	1.733
MAE	0.0073	1.134	0.0092	1.358	0.0126	2.304

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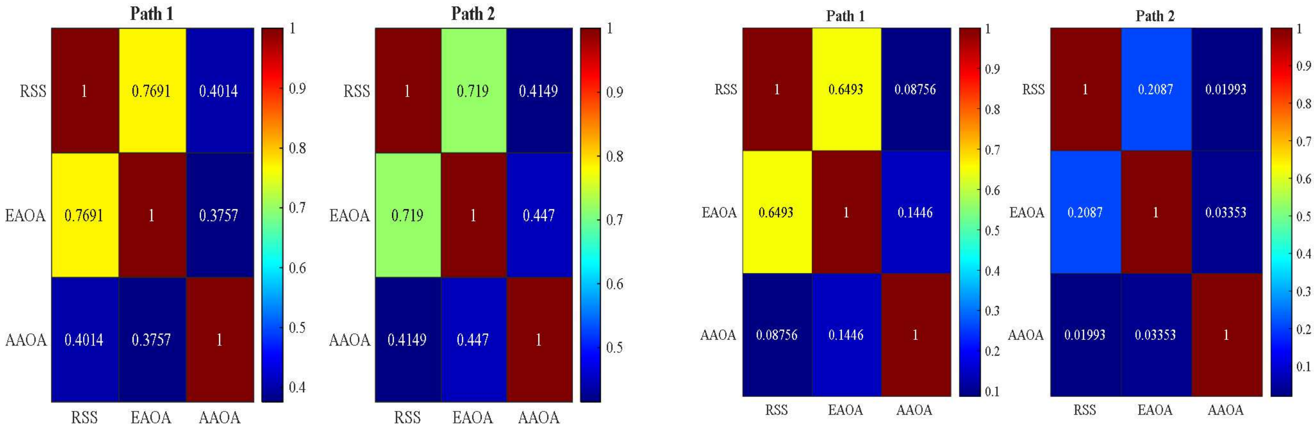
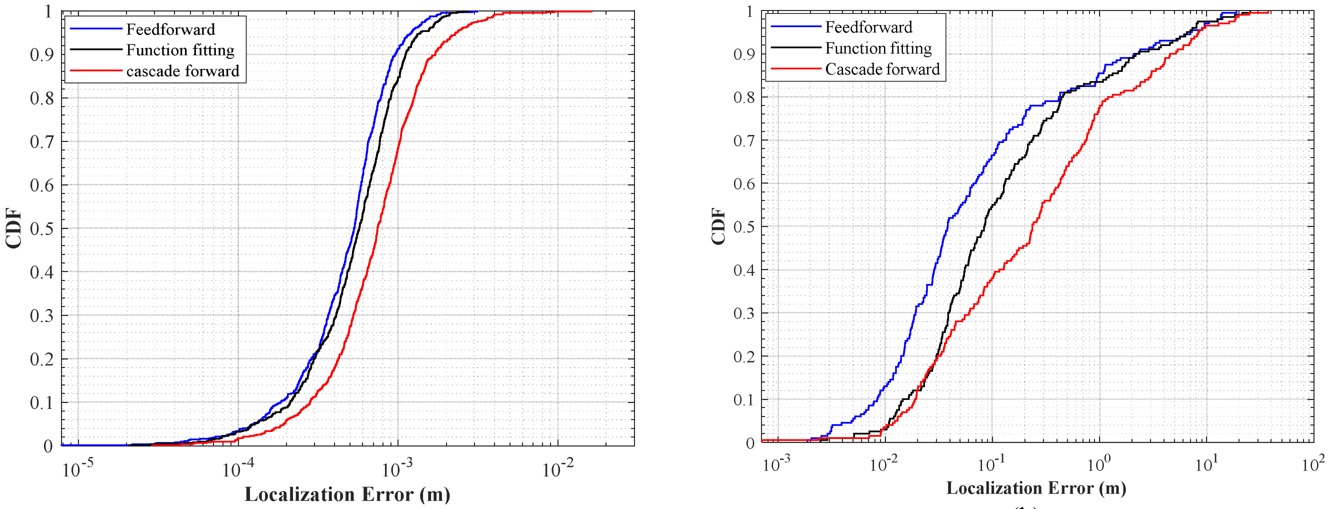


(a) (b)

Fig. 2 Correlation coefficient heatmap (a) LOS, and (b) NLOS



(a) (b)

Fig. 3 CDF of vehicle localization error (a) LOS, and (b) NLOS

C. *Evaluation with Uncertainties*

In order to validate the robustness of the proposed localization method, the developed feedforward DNN, which has achieved the best performance over the function fitting DNN and cascade forward DNN, is tested by using the corrupted dataset. These datasets are generated with random distribution uncertainties as explained earlier.

Fig. 4 shows the CDF of the localization error of the proposed feedforward DNN with the corrupted datasets for LOS and NLOS scenarios. As can be inferred from the CDF, the uncertainties have more impact on localization accuracy of the NLOS scenario comparing to LOS scenario. For example, at 70% of the NLOS vehicles were having localization error more than 2m; meanwhile, 70% of the LOS vehicles were having localization error more than 0.1m.

In conclusion, the localization accuracy of the machine learning method can be more affected by uncertainties, especially in NLOS scenario. As recommendations for future works to handle this issue, extracting more features; moreover, design robust DL model by using different structure.

VI. Conclusion

Vehicle localization in urban environments is a highly complex task. The performance of the current localization method is poor in such environments. However, this work proposed a vehicle localization based on fingerprinting method of mm-Wave including RSS and angular jointly. The DNN is utilized to predict the location of the vehicle at LOS and NLOS scenarios. In particular, three types of DNN namely, feedforward DNN, function fitting DNN, and cascade-forward are trained and tested. A realistic ray tracing method is used to generate the mm-Wave fingertips. The impact of the vehicle speed on the accuracy of the proposed method is further studied. The results showed that the proposed method based on feedforward DNN provided the best vehicle localization accuracy for LOS and NLOS scenarios. Whereas, the accuracy of this method at NLOS scenario was strongly degraded when the developed DNN is tested by using corrupted dataset. For future works, we would consider generating features and different deep learning models to improve the robustness of the proposed method.

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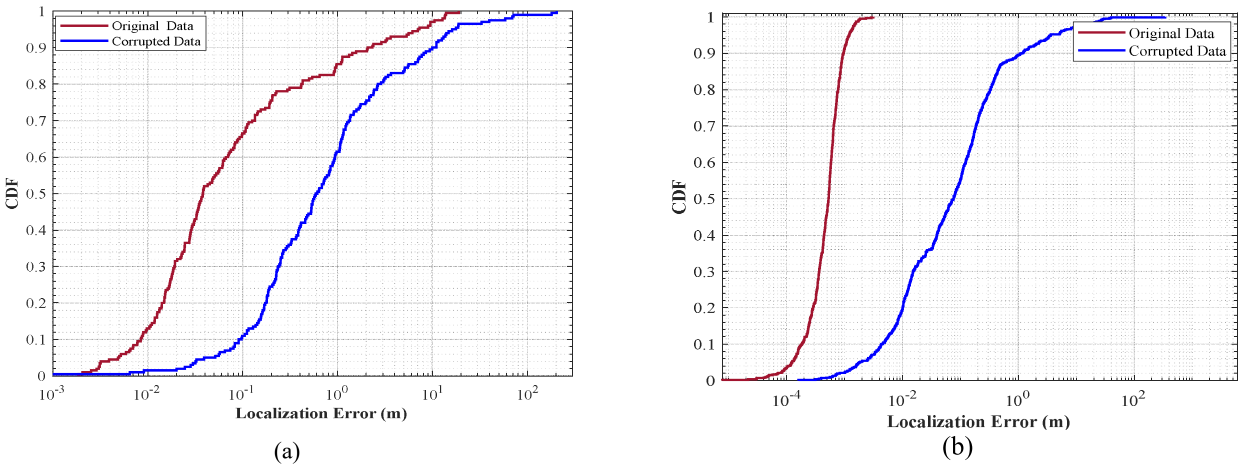

Fig. 4. CDF of the localization error under uncertainties for feedforward DNN. (a) LOS, and (b) NLOS

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