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Lab to Multi-Scene Generalization for Non-Line-of-Sight Identification with Small-Scale Datasets

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***Abstract*—Ultra-wideband (UWB) wireless indoor positioning systems rely on time of flight (TOF) to estimate distances but can be biased and miscalculated due to non-line-of-sight (NLOS) transmission channels in complex environments. Therefore, to remove errors, several machine learning techniques have been proposed for identifying NLOS signals from Channel Impulse Responses (CIRs). However, as CIR signals could be heavily influenced by various environments, current NLOS classifiers are not universal to provide satisfactory accuracy for new scenarios and require detailed measurements on a large number of CIRs for training. Hence, we propose a generalization method based on data augmentation via noise injection and transfer learning to allow the deep neural network (DNN) trained under a lab condition to be applied to various and even harsh practical scenarios with the need to measure massive training data minimized. This paper presents the first demonstration that it is effective to utilize a lab-based pre-trained DNN for real-world transfer and white Gaussian noise data augmentation for ML-based NLOS identification on UWB CIRs to address the problem when it is not feasible to measure sufficient training data. Our testing results show that in two scenarios, corridor and parking lot, with only 50 CIR signals as the training set, the accuracy of the NLOS identification model after applying the proposed method is increased from 84.4% to 98.8% and from 81.1% to 97.1%, respectively.**

***Impact Statement*—In this paper, we propose a robust and data-efficient DNN-based method for identifying non-line-of-sight (NLOS) signals within ultra-wideband (UWB) indoor positioning signals to overcome distance estimation errors. For applications in a new environment or generalization across multiple environments, the need for sufficient data to train the DNN model can be largely lowered and higher accuracy can be offered. Furthermore, with our approach, the realization of accurate NLOS identification becomes possible in some harsh scenarios where collecting a large amount of data is costly, time-consuming, or even impossible. In addition, we have investigated the possibility of applying noise injection to augment channel impulse response signals (CIRs) and to deal with environmental noise.**

***Index Terms*—Indoor localization, UWB, NLOS identification, Machine Learning, DNN, CIR.**

I. Introduction

THE indoor localization system plays an essential role in the Internet of Things (IoT) applications, such as automatic vehicles, healthcare devices, logistics, industrial production, and wireless sensor networks, where accurate real-time position measurement is needed [1] – [5]. For example, smart unmanned robots will play an important role in future hospitals [6]. Advanced positioning systems immediately locating patients help automated guided vehicles transport medical materials or patients themselves timely in an emergency, and tracking patient activities also optimizes individual treatment [7]. Due to the attenuation of obstacles such as concrete walls and windows, lots of indoor localization methods have been explored rather than those for outdoor environments (e.g., Global positioning system (GPS) and global navigation satellite system (GNSS)). These indoor techniques cover Wi-Fi, Bluetooth, Infrared, and ultra-wideband (UWB) [1]. The localization system using UWB measures time-of-flight (TOF) to estimate the distance to the target. For a precise calculation of converting TOF to distance, the transmission between the transmitter and receiver must be in a line-of-sight (LOS) condition. Otherwise, as illustrated in Fig. 1(a), a non-line-of-sight (NLOS) transmission caused by signal reflection can delay the TOF of the UWB measurement and hence add a positive bias to the estimated distance. However, NLOS signals are inevitable in realistic environments due to any obstacles by objects and walls and cause positioning errors [8]. Therefore, for this issue, a common solution is to detect LOS and NLOS propagation during positioning so that those false results can be corrected with an error model or simply filtered out.

Lots of NLOS identification techniques have been investigated throughout the literature by statistical analysis of channel characteristics. [8] - [16]. Recently, the rapid development of machine learning (ML) algorithms and their excellent classification performance has inspired research in NLOS identification technology. With the support vector machine (SVM), an efficient ML model, either the extracted features from channel [17], [18], or the channel impulse response (CIR) signal [19] can be used to identify NLOS with over 90% accuracy. More ML methods, including deep neural network

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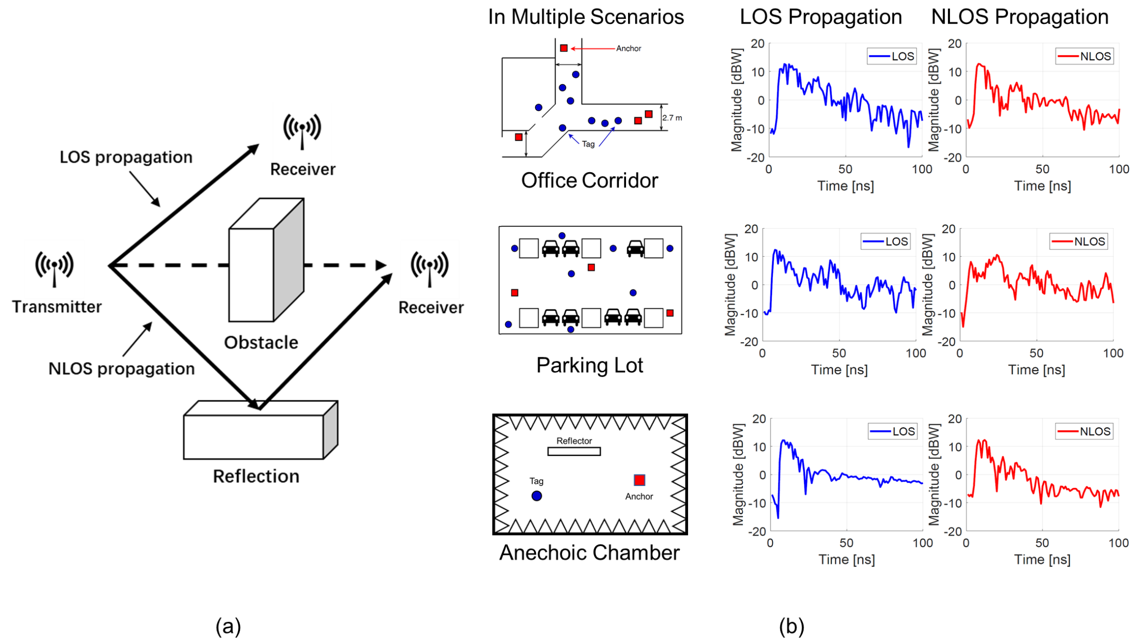

Fig. 1. Overview of the NLOS identification system: (a) NLOS and LOS communication, (b) Examples of measured CIRs in multiple scenarios.

(DNN) [20], convolutional neural network (CNN) [21] - [23] and long short-term memory (LSTM) [24], are adopted for NLOS identification by leveraging the CIR data and reported to achieve higher classification accuracy than SVM [21].

However, it has been noticed from previous experiments [14], [25], [26] that the variation of environments has a significant influence on measured UWB signals, and CIRs from three different scenarios vary, as shown in Fig. 1. Specifically, most ML-based NLOS classifiers have limited generalisability and they must be trained and applied in the same scenarios. Otherwise, their performance in an unmeasured and untrained scenario degrades due to the environmental noise [26]. As NLOS transmission results from obstacles in the environment, channel statistic features for ML models to analyze are dependent on scenario settings. Thus, every time the applied scenario changes, it is a must to collect a massive amount of data and re-train the model, which can be time-consuming, complicated, or even impossible in some harsh cases due to limitations including infectious diseases, radiation, and chemical toxicity.

Following the lab-to-real-world transfer concept, the DNN NLOS classifier pre-trained in an anechoic chamber as a lab condition with sufficient training data is generalized and transferred to the practical scenarios with data augmentation emulating the environmental influence. To adapt the lab-based NLOS classifier to a new targeted scenario, only a minuscule amount of data (i.e., 50 sets of CIRs) needs to be re-measured and scaled up by Gaussian noise injection as a form of data augmentation. The dataset after augmentation is able to fine-tune the initial DNN model via transfer learning technique to obtain promising NLOS identification performance in the targeted scene. According to our experiment results, the model generalized by our proposed technique can achieve 98.8% and 97.1% accuracy in new scenarios, a corridor and a parking lot, respectively. As a comparison, without the proposed method and under the same condition of prior data, the DNN model trained from such small-scale data would have only 84.4% and 81.1% accuracy.

Several previous studies also focus on this problem and provide some solutions, such as transfer learning [26]. Compared to others, the contributions of our work lie in:

- The proposed DNN-based model with generalization can identify NLOS in multiple scenarios to assist indoor localization with superior accuracy, compared with other existing ML-based methods.
- We propose the lab-to-real-world transfer concept to realize DNN-based NLOS identification in practical scenarios where it is difficult to collect a large amount of data for training. By generalizing the lab-based model, the demand for and cost of measurement of training data for NLOS identification are largely reduced.
- Our work is the first study and experiment to investigate and validate the possibility of introducing data augmentation via injecting noise to CIRs for the enhancement of generalization in ML-based NLOS identification.
- By injecting noise into CIRs as training input, it is found that the robustness of the model for NLOS classification in a noisy condition is improved.

As a result, we address the engineering problem of applying ML-based methods in real-world scenarios where it is difficult to obtain a large amount of data from measurements.

II. NLOS Identification Approach

A. Channel Impulse Response

The channel impulse response (CIR) is the power output profile over the measured channel in response to an impulse

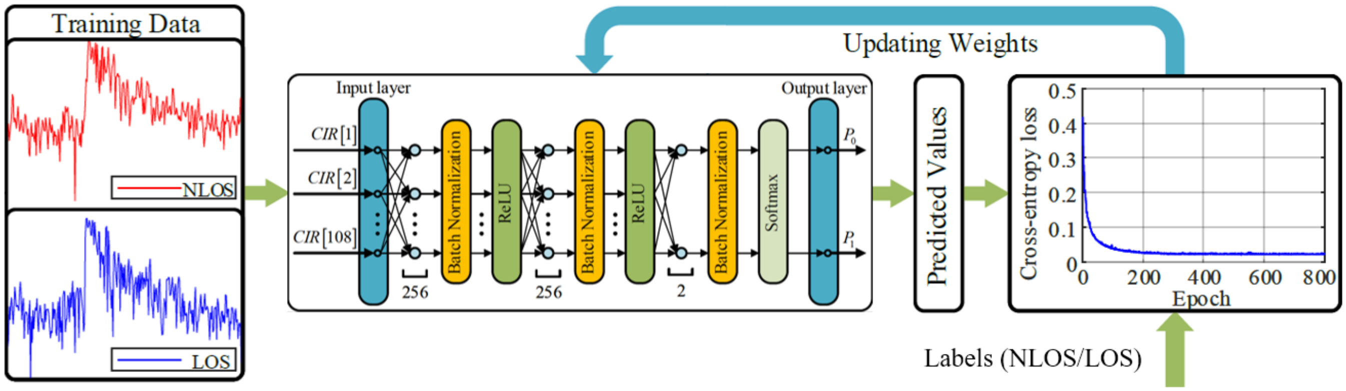

Fig. 2. The proposed DNN model architecture for NLOS identification and the training process.

as a function of time delay, which can be given by [27]:

$$h(t) = \sum_{i=1}^{n} \beta_i \delta(t - \tau_i) \tag{1}$$

where n is the number of multi-paths, and β_i and τ_i represent the attenuation coefficient and delay of the i_{th} path, separately. Compared to LOS, NLOS transmission could introduce differences in features of CIR. For example, the first path component is always stronger than the other path as it is received first with the shortest distance. Nevertheless, under an NLOS condition, the signal is reflected and delayed, resulting in a weaker first path component and a higher delay term. These characteristics related to NLOS can be statistically analyzed by ML-based models after training with labelled CIRs. Thus, the DNN model can be designed for NLOS classification based on CIR [20]. Furthermore, instead of analyzing the selected features of CIR, the complete CIR waveform can be used as the input to an ML-based model for NLOS identification since the model itself can extract needed features, making data augmentation by noise injection possible [19], [21], [24].

One of the challenges of the CIR-based NLOS classifier is its sensitivity to the variation of environments, causing its limited generalizability and poor accuracy in an untrained scenario. It is known that amplitude and delay terms of multi-path components are determined by the characteristic of the transmission paths, which are dependent on the scenario settings. Thus, a new scenario with different obstacles, shapes and distances may result in variation in received power and delay of LOS and NLOS conditions, leading to misclassification of NLOS based on criteria studied from previous scenarios. Generally, if an ML model is expected to be applied in a scenario, CIR data belonging to that scenario is required for training. However, we propose that the requirement could be simplified by data augmentation and transfer learning so that just small-scale CIR data in a new scenario should be measured.

B. Deep Neural Network

In the future B5G and 6G scenarios, it is necessary to pursue low-latency and low-power applications when deploying NLOS recognition models into IoT devices. Thus, instead of the existing complicated CNN or LSTM network, we consider the low-complexity DNN network as our feature extractor and NLOS classifier. DNN is a well-known classification tool [28] and is employed for NLOS identification [20]. It is a mathematical model built up around so-called neurons, where model weights for passing to other neurons are determined during training to end up with the classification based on the input vector.

The network architecture is a simple 3-layered feed-forward neural network illustrated in Fig. 2, with rectified linear unit (ReLU) activation functions between the hidden layers, which have a size of 256 perceptrons, 256 perceptrons and 2 perceptrons, separately. The layers used are fully connected (FC) layers and the batch normalization (BN) layers, connected by the activation function as seen in Fig. 2. In the FC layer, the output of the i_{th} FC layer is defined as

$$y_i = W_i x_i + B_i, \tag{2}$$

where x_i is the input feature, B_i reflects bias, and W_i denotes the weights. The output of the i_{th} FC layer is passed the BN layer, which can be expressed by

$$\hat{y}_i = \gamma \frac{y_i - \mathrm{E}\left[y_i\right]}{\sqrt{\mathrm{Var}\left[y_i\right] + \varepsilon}} + \beta, \tag{3}$$

where γ and β represent the new mean and variance of the input data, respectively. Besides, ϵ is a constant parameter that prevents the denominator from being zero. The ReLU activation function is applied to the output of the first BN layer, which effectively avoids gradient disappearance and gradient explosion when training the model. The ReLU function is defined as:

$$\mathrm{ReLU}(x) = \max(x, 0), \tag{4}$$

where x represents the input of the ReLU function. Finally, the Softmax function is used as the last layer's activation function. It outputs a vector of two confidence values as output for determining the signal to be either LOS or NLOS and is defined as:

$$S_i(x) = \frac{e^i}{\sum_j e^j}. \tag{5}$$

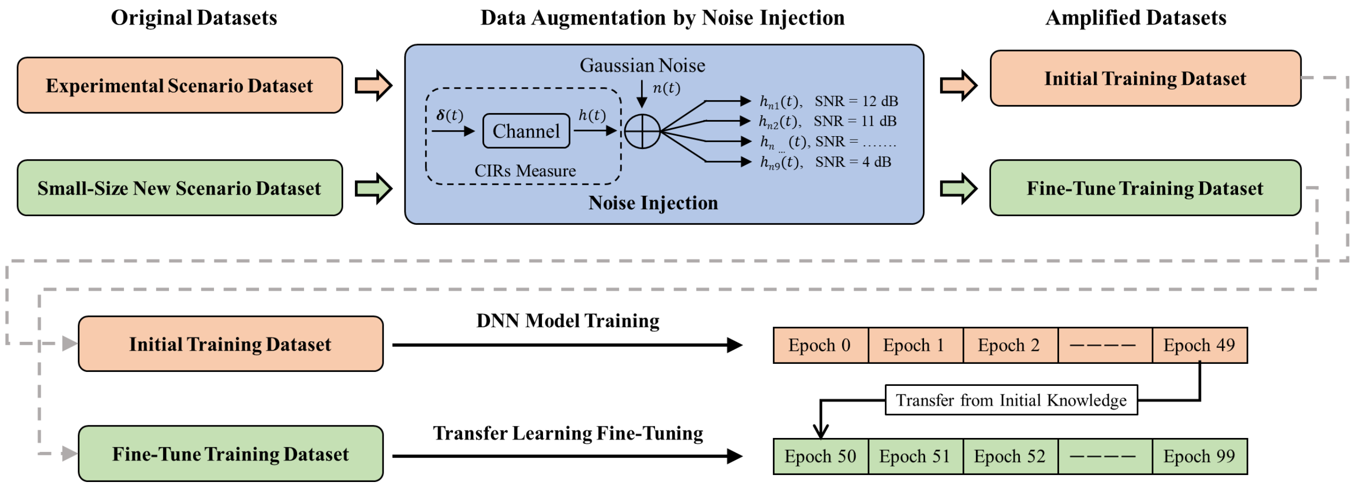

Fig. 3. The proposed generalization method for NLOS identification in multiple scenarios through transfer learning and data augmentation by noise injection.

To evaluate the performance of the network in training, it is chosen to use the loss function cross-entropy loss in combination with a soft-max function:

$$\ell(k, \boldsymbol{\pi}) = -\ln\left(\frac{\exp \pi_k}{\sum_i \exp \pi_i}\right). \tag{6}$$

where k is the index of the target class, and $\boldsymbol{\pi}$ are the unnormalized posterior class probabilities which are the output of the last layer of the network.

The optimizer is chosen to be Stochastic Gradient Decent with a learning rate found empirically to 0.05, which seeks to minimize the loss criterion.

Fig. 2 shows the designed DNN model and the basic training process diagram of this work, where labels are known as expected values. As seen from the figure, the training process would end when the loss between labels and predicted values is no longer reduced or reaches a preset threshold.

The DNN model is pre-trained by the CIR data collected in an anechoic chamber, where basic LOS and NLOS conditions are created manually with reflectors to ensure its universality. When it comes to NLOS identification in a new scenario where only a small-scale training dataset should be measured, the initial model can be fine-tuned by transfer learning using sufficient data after augmentation. The process of realizing generalization in a new scenario is shown in Fig. 3.

C. Data Augmentation

Data augmentation is a common method to increase the amount of data to fulfil the requirement of data training, avoid overfitting and improve the accuracy and robustness of the DNN [29], [30]. A number of modified copies can be generated by trimming the original data using geometric transformation or adding noise to compensate for the lack of training data. In particular, jittering data with noise has been reported to be effective in improving the generalizability of deep learning models [31], [32]. Thus, this technique is powerful for some applications requiring a large training dataset but with the difficulty of collecting it, such as computer vision, biological signal, and medical image analysis [33] - [36]. In order to train an NLOS identification model generalized in multiple scenarios, extensive datasets should be measured in each corresponding scenario. It is complicated, costly, and time-consuming for lots of measurement equipment to be set up whenever a new environment comes up, and the quick application of NLOS identifier in harsh scenarios is unachievable. Although some data augmentation techniques for image analysis are not suitable for CIR signals, some for time series data are available. In this work, we employ the noise injection method by adding Gaussian white noise, which is proven to be effective through comparative experiments in the following sections.

As shown in Fig. 3, we modify the copies of the original CIR signals by injecting white Gaussian noise to create new training data. The additive noise is generated based on the signal-to-noise ratio (SNR) against the existing signals to guarantee that the signal power is always greater than the noise power. The probability density function of Gaussian distribution is defined by:

$$p(x) = \frac{1}{\sigma\sqrt{2\pi}} e^{-\frac{(x-\mu)^2}{2\sigma^2}}, \tag{7}$$

where σ and μ^2 are its mean and variance, respectively, and it can be notated as $\mathcal{N}(\mu, \sigma^2)$. And SNR is given by:

$$SNR = \frac{P}{N}, \tag{8}$$

where P is the signal power and N is the noise power. Therefore, the variance of the expected noise, as well as its power, can be determined as

$$\sigma^2 = N = \frac{P}{SNR}. \tag{9}$$

With $\mu = 0$, the distribution of the additive white Gaussian noise for data augmentation n is given by:

$$n = \sigma \times \mathcal{N}(0,1) = \sqrt{\frac{P}{SNR}} \times \mathcal{N}(0,1). \tag{10}$$

Based on equation (1), the CIR after adding noise, which is expected to emulate the actual measure of CIR with environmental noise, can be written as:

$$h_n(t) = \sum_{i=1}^{n} \beta_i \delta(t - \tau_i) + n(t). \quad (11)$$

Totally, 9 sets of augmented data are generated with the SNR ranging from 4 dB to 12 dB.

Both the chamber dataset and the small-size dataset of a new targeted scenario are augmented. The former is augmented for pre-training the initial model, while the latter is for fine-tuning. It is crucial to apply data augmentation to the chamber dataset to maintain consistency with the augmented dataset of the new scenario, which may facilitate the process of fine-tuning and final accuracy. Some samples of LOS and NLOS CIR signals with and without additive noise from three scenarios are illustrated in Fig. 4 - 6.

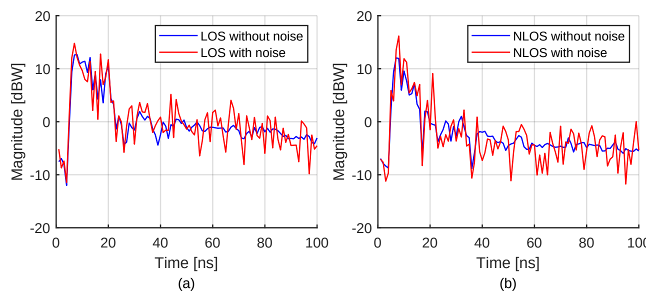

Fig. 4. Original CIR signals from the anechoic chamber and CIR signals with additive noise, (a) LOS and (b) NLOS.

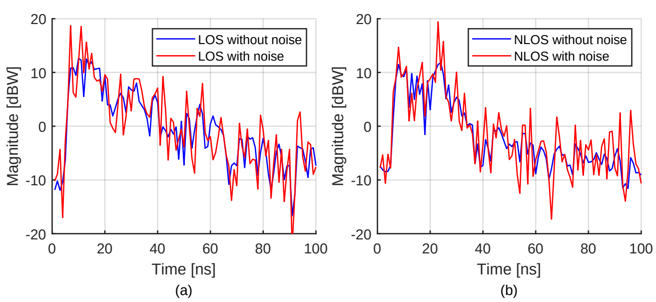

Fig. 5. Original CIR signals from the corridor and CIR signals with additive noise, (a) LOS and (b) NLOS.

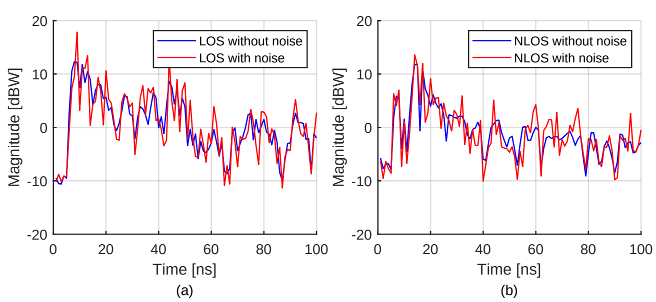

Fig. 6. Original CIR signals from the parking lot and CIR signals with additive noise, (a) LOS and (b) NLOS.

D. Transfer Learning

To minimize the need for training data in real-world scenarios and save time in model training, transfer learning is essential to adapt an existing model from a lab condition to a related problem [37] - [39]. Inspired by virtual-to-real-world transfer, we propose lab-to-real-world transfer to minimize the need for a large amount of data in new environments. From an anechoic chamber lab, NLOS and LOS conditions can be artificially created and then measured to pre-train an initial DNN model. By leveraging transfer learning, the pre-trained model can be simply fine-tuned for real-world NLOS identification in a new target scenario. Besides, cooperation with data augmentation can further enhance the efficiency in the usage of data and increase the accuracy of the final DNN model.

Transfer learning in our proposed generalization method of Fig. 3 is implemented by a parameter sharing approach, which initializes the network by the parameters from the pre-trained model. We use 50 epochs to pre-train the initial model with the chamber dataset. For the application in a new scenario, the pre-trained model is set as the initial network for training by another 50 epochs using the dataset from the targeted scenario. The number of training epochs should be tuned regarding the practical performance. It should be noted that the data for pre-training the initial model is collected in an anechoic chamber, where the UWB anchor and tag with the reflector are set manually to create LOS and NLOS transmission channels for CIR measurement. Under such a lab condition, a large size of data can be collected efficiently, and the influence of the environment is largely suppressed. In addition, we also apply data augmentation through noise injection to the anechoic chamber data. As it is beneficial to expose the initial DNN model to the noise, which reduces the difficulty of adapting to noisy signals during fine-tuning.

III. MEASUREMENT SETUPS

The training and testing CIR data is measured and generated by UWB EVB1000 kits [40], [41] integrated with a Decawave DW1000 transceiver IC. Each board for measurement is mounted on a bracket at a height of 1.6 m. The UWB transceiver boards, divided into tags and anchors, are settled and changed several times at different positions to create LOS and NLOS paths depending on the measured scenarios. The collected signals are first processed by the evaluation board. As introduced in the previous section, the experiments are carried out in three scenarios: anechoic chamber, corridor, and parking lot, which are illustrated in Fig. 7.

Two EVB1000 kits are set as a transmitter and a receiver to collect the CIRs in the 8 m $\times$ 9 m anechoic chamber of Fig. 7(a). To create NLOS paths, three metal plates with the sizes of 1 m $\times$ 1 m, 0.35 m $\times$ 0.26 m and 0.23 m $\times$ 0.17 m are placed as obstacles and reflectors.

Three EVB1000 kits were used to measure the CIR data in the corridor of Fig. 7(b), which has brick or concrete walls on both sides. Such a scenario can emulate the real multipath environments of localization applications, and the NLOS path is created under the actual environment due to the shape of the corridor.

Similarly, CIRs are collected by three EVB1000 kits in an underground parking lot, as shown in Fig. 7(c). This concrete

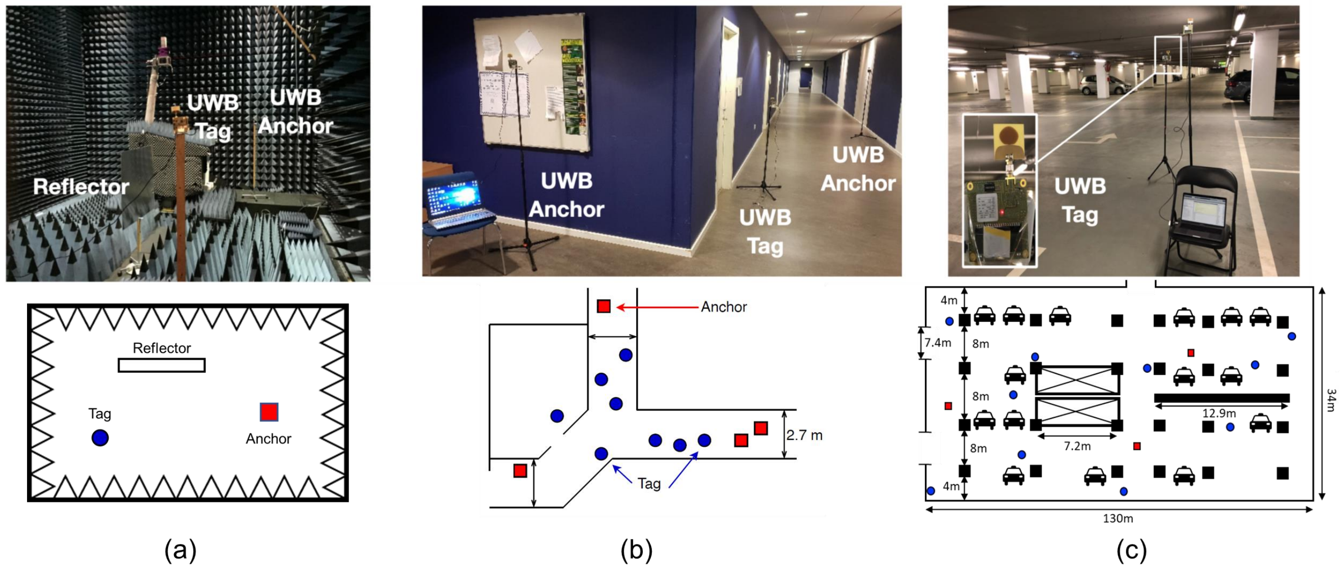

Fig. 7. Measurement Setups in: (a) anechoic chamber, (b) office corridor, and (c) parking lot.

underground space has 130 m in length, 34 m in width, and 2.5 m in height. As shown in the figure, black squares represent pillars with 0.78 m in width. Concrete walls, cars, and pillars result in LOS and NLOS paths in this typical multi-path environment.

Eventually, the retrieved CIRs are aligned to the leading edge of CIRs, and the available data is cropped to a length of 100 data points for convenience. For each scenario, training and testing datasets are established by 700 and 300 sets of CIRs, separately, with a ratio of 7:3. Besides, datasets for training and testing are balanced, with an equal proportion of LOS and NLOS data in both groups. During the DNN training phase, a subset with the desired number of CIRs, depending on the conditions and requirements of experiments, would be extracted from the training group. Samples of LOS and NLOS CIRs in three scenarios are presented in Fig. 1(b).

IV. Results and Discussion

To demonstrate the significance and improvements of the proposed method for small-scale data application in a variety of scenarios, this section covers experiment results and their related discussion, including:

- Benchmark performance of typical ML models without the proposed generalization method, under the condition where only a small amount of training data is available.
- Demonstration of NLOS identification accuracy improvements due to the proposed method on a small-scale dataset.
- Experiment on additional data augmentation methods including colour noise, clipping, and warping, for DNN-based NLOS identification model.
- Comprehensive comparison of existing ML-based approaches for NLOS identification from the literature, including SVM [19], CNN [21] and CNN+LSTM [24].
- Computational complexity analysis of the proposed method.

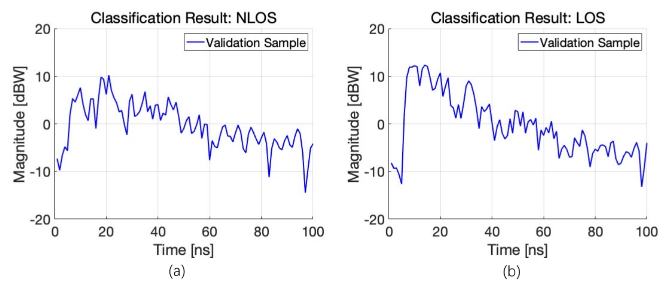

Fig. 8. Validation of the classification model with (a) an NLOS sample and (b) a LOS sample.

- Discussion of the possibility of reusing the available training data from other scenarios.
- Demonstration of noise immunity enhanced by the proposed method.

The ML models in this work are implemented by scikit-learn and Keras libraries based on Python 3.7.11 running on MacBook Pro M1. An example that validates the proposed method to generate classification results for CIR inputs is visualized in Fig. 8.

The results of NLOS identification can be grouped into four categories, true positive (TP), true negative (TN), false positive (FP) and false negative (FN), which represent correct NLOS prediction, correct LOS prediction, incorrect NLOS prediction and incorrect LOS prediction, respectively. Then, based on statistics results, the classification performance of ML-based models is evaluated by metrics of accuracy, precision, recall, F_1-score, which can be calculated by:

$$Accuracy = \frac{TP + TN}{TP + FP + TN + FN}, \tag{12}$$

$$Precision = \frac{TP}{TP + FP}, \tag{13}$$

$$Recall = \frac{TP}{TP + FN}, \tag{14}$$

TABLE I
BENCHMARK IDENTIFICATION ACCURACY OF ML METHODS IN MULTIPLE SCENARIOS WITH A TRAINING SET SIZE EQUAL TO 50 AND 200.

ML Methods		SVM			DNN		
Test Scenarios		Chamber	Parking Lot	Corridor	Chamber	Parking Lot	Corridor
Training Scenarios Training Set Size = **50**	Chamber	**93.0%**	63.9%	80.1%	73.9%	51.3%	56.2%
	Parking Lot	47.1%	**92.1%**	43.2%	45.2%	81.1%	56.2%
	Corridor	76.8%	54.3%	**91.8%**	65.0%	66.4%	84.4%
Training Scenarios Training Set Size = **200**	Chamber	93.0%	64.3%	74.4%	**96.2%**	52.1%	68.7%
	Parking Lot	53.5%	93.6%	55.6%	51.8%	**98.0%**	49.2%
	Corridor	71.2%	80.0%	96.8%	62.3%	83.5%	**98.6%**

$$F_1 = \frac{2 \times Precision \times Recall}{Precision + Recall}. \quad (15)$$

A. Benchmark Performance of ML Methods in Multiple Scenarios

We first test the benchmark multi-scene performance of the chosen ML method, DNN, along with SVM, a widely used ML technique for NLOS applications, with a limited scale of the training set. As shown in Table I, without proposed generalization technique, The size of the training set is another issue for NLOS identification of ML-based methods as revealed by the benchmark performance. With 50 sets of CIRs, DNN can only attain 81.1% and 84.4% accuracy in trained scenarios of parking lot and corridor, respectively. The contrast between validation and train loss curves without data augmentation in Fig. 9 indicates the basic model is underfitted at around the 20th epoch and overfitted after the 20th epoch due to the lack of training data. With a small training set size, SVM models could perform relatively better but still unsatisfactorily, especially with 92.1% and 91.8% accuracy for the classification in the parking lot and corridor. However, if the training set size increases to 200, the accuracy of DNN models can achieve higher accuracy than SVM, around 96.2% to 98.6% in the respective trained scenarios. The results with different training set sizes demonstrate DNN model demands sufficient training data to reach its upper limit capability for NLOS identification, which can outperform SVM. To sum up, the benchmark results indicate the limited generalizability of ML-based methods, and a large amount of training data is required for precise NLOS identification in multiple scenarios with the traditional methods.

B. Improvements by Data Augmentation and Transfer Learning

Illustrated in Fig. 10 and 11, the proposed method, combining the advantages of transfer learning and data augmentation through noise injection, is able to assist the DNN model to generalize in different scenarios with a small-scale of data. To examine the performance, the number of CIRs for training from the targeted scenario is restricted to 50, and 450 sets from the anechoic chamber are available for pre-training.

As the benchmark, the basic DNN model can only provide 84.4% and 81.1% accuracy in the corridor and parking lot, separately. For a fair contrast analysis, the chamber dataset for pre-training is also treated as one of the controlled inputs to the model. Employing transfer learning with chamber dataset can

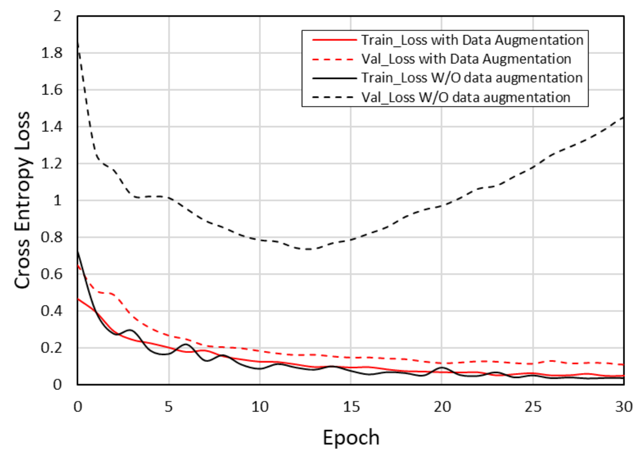

Fig. 9. Cross entropy loss of training and validation with and without data augmentation on 50 sets of original CIRs.

increase the accuracy to 93.3% and 92.7% for the corridor and parking lot compared to simple mixing. Similarly, with noise augmentation, the NLOS recognition accuracy is improved by about 10% in the same scenario after data augmentation by injecting noise to increase the size of the training set by a factor of 9 (50 to 450 sets). Furthermore, the loss change during the training phase after applying data augmentation is shown in Fig. 9. It suggests the underfitting problem can be addressed by data augmentation with the gap between train and validation loss minimized compared to that without data augmentation. It can be concluded that under the same prior condition of training data size (450 sets of data from the chamber + 50 sets of data from a new scenario), data augmentation and transfer learning for DNN can dramatically enhance its NLOS identification accuracy.

Thus, as we proposed, both data augmentation and transfer learning are essential for generalization with small-scale data. The results of experiments in DNN+TL groups demonstrate that injecting noise to augment either the pre-train data (chamber data) or fine-tune data (corridor or parking lot data from multiple new scenes) can be advantageous. When both datasets (pre-train and fine-tune) are amplified, the accuracy could reach the maximum in our experiments. For the fine-tuning dataset, on one hand, the augmentation provides sufficient training data for the model. On the other hand, for the pre-training dataset, we deduce that the model could adapt to the additional noise in advance. Consequently, compared to using the transfer learning technique only, the introduction of the data augmentation exhibits an advantage of around 5% in

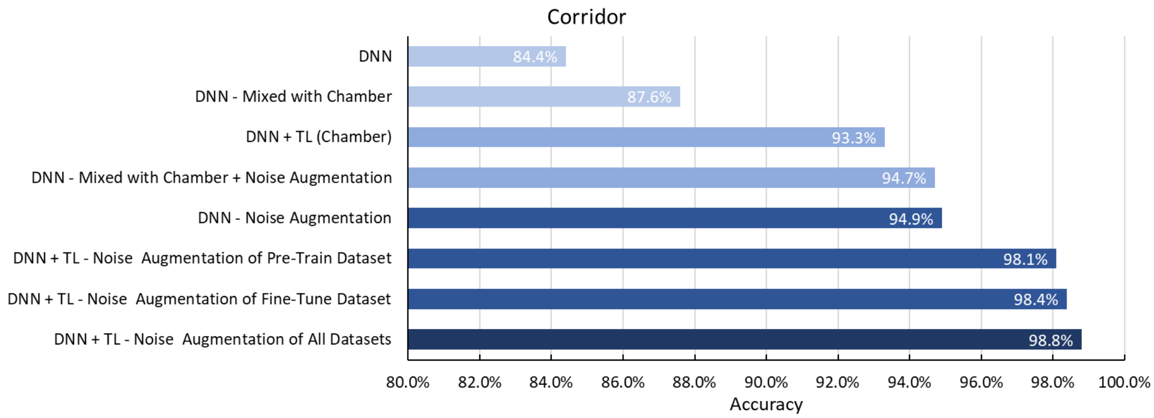

Fig. 10. Identification accuracy of DNN in the corridor with different generalization methods using 50 sets of training data. (TL: transfer learning)

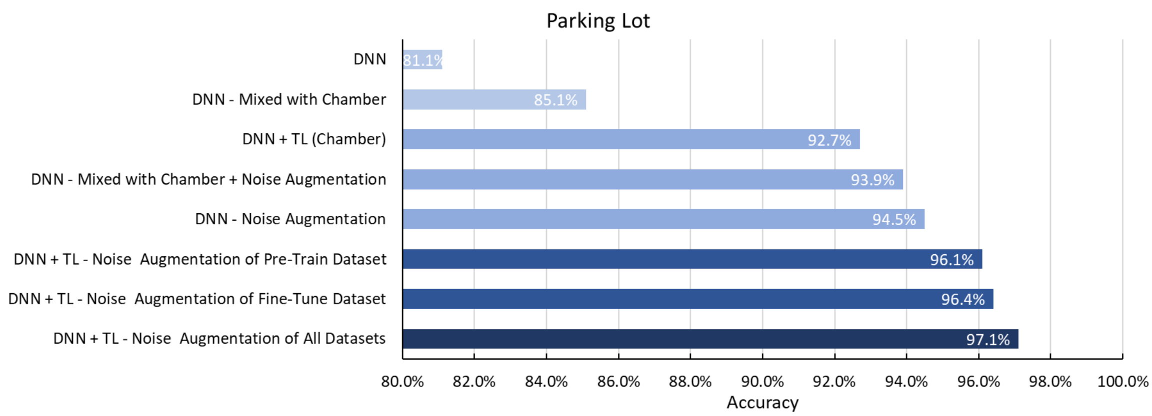

Fig. 11. Identification accuracy of DNN in the parking lot with different generalization methods using 50 sets of training data. (TL: transfer learning)

accuracy.

Therefore, a combination of data augmentation and transfer learning is proposed to address the challenges of requiring large NLOS identification training data in a variety of scenarios. As shown in Fig. 10 and 11, the NLOS identification of the DNN model can achieve up to 98.8% and 97.1% accuracy for the corridor and parking lot, respectively. Furthermore, considering the rise in accuracy from the benchmark (84.4% and 81.1%), our approach is enormously effective for a DNN model to be generalized to a new environment with demand on training data (i.e. 50 CIRs).

C. Comparison of Data Augmentation Techniques

Except for noise injection using AWGN, other data augmentation techniques including using colour noise source [42], [43], data clipping and data warping [29], [44], [45] are worth researching on their influence on CIRs and the DNN model for NLOS identification. To implement these augmentation techniques, colour noise (white, pink, brown, blue, and purple) are generated in MATLAB and added to the CIRs. Data clipping is performed by sliding a window on CIR to take 70 to 80 random samples (100 in total) with others padded by zero. Besides, data warping is realized by first clipping 50 samples and then stretching them by a ratio of 2. Finally, an equal amount of training data after augmentation would be obtained from 50 original CIRs.

The results of several tested data augmentation methods for NLOS identification in the corridor and parking lot are included in Table II. For all evaluation metrics of NLOS identification, white noise ranks first in both corridor and parking lot, and hence it is chosen for data augmentation as our proposed method. For other colour noise, the overall performance in corridor may actually degrade, while a rise of 2-5% in recall rate can be found in parking lot. These two opposing trends indicate there is uncertainty in the outcome of injecting coloured noise with non-constant power density in the frequency domain. Furthermore, it is noticed that applying data clipping only cannot assist NLOS identification with a small-scale set of data, but combining data clipping and warping gives a relatively competitive performance. Especially, the accuracy and recall rate from 93.2% and 92.8% jumps to 95.7% and 95.1% in corridor, and from 92.8% and 88.0% to 94.9% and 92.5% in parking lot.

D. Comparison of Existing ML-based NLOS identification Methods

To have a comprehensive evaluation of the performance of the proposed method, we choose some ML-based methods from previous research as the comparison in Table III for the corridor and IV for the parking lot. With only a small-scale dataset available (50 sets of CIRs), the accuracy of ML-based

TABLE II
PERFORMANCE METRICS COMPARISON OF AUGMENTATION METHODS

Augmentation Method	Accuracy	Precision	Recall	F1-score	Accuracy	Precision	Recall	F1-score
	Scenario: Corridor				**Scenario: Parking Lot**			
W/O Augmentation	93.2%	93.7%	92.9%	0.932	92.8%	97.4%	88.0%	0.924
White Gaussian Noise	**98.8%**	**98.4%**	**99.1%**	**0.988**	**97.1%**	**98.5%**	**95.6%**	**0.970**
Pink Noise	86.8%	82.8%	93.0%	0.876	93.0%	94.4%	91.4%	0.929
Brown Noise	89.3%	89.7%	88.8%	0.892	88.9%	88.0%	90.1%	0.891
Blue Noise	91.6%	93.7%	89.2%	0.914	91.3%	90.9%	91.9%	0.914
Purple Noise	91.5%	92.3%	90.6%	0.914	93.9%	94.5%	93.2%	0.938
Clip	87.0%	93.9%	79.2%	0.858	91.9%	93.3%	90.4%	0.918
Clip + Warp	95.7%	96.2%	95.1%	0.956	94.9%	97.2%	92.5%	0.948

TABLE III
PERFORMANCE METRICS COMPARISON OF EXISTING AND PROPOSED NLOS CLASSIFICATION METHODS FOR CORRIDOR SCENARIO

Method	Accuracy	Precision	Recall	F1-score
SVM	92.1%	91.8%	96.4%	0.941
SVM - Noise Augmentation	93.9%	92.9%	96.3%	0.945
CNN	92.3%	87.6%	98.6%	0.928
CNN - Noise Augmentation	96.2%	94.7%	98.2%	0.963
CNN + LSTM	86.4%	89.1%	84.4%	0.860
CNN + LSTM - Noise Augmentation	96.4%	96.8%	96.4%	0.965
DNN	84.4%	88.6%	78.9%	0.835
DNN - Noise Augmentation	94.9%	91.4%	98.9%	0.950
DNN + TL	93.2%	93.7%	92.9%	0.932
DNN + TL - Noise Augmentation	**98.8%**	**98.4%**	**99.1%**	**0.988**

Reference of ML-based methods: SVM [19], CNN [21] and CNN+LSTM [24].

TABLE IV
PERFORMANCE METRICS COMPARISON OF EXISTING AND PROPOSED NLOS CLASSIFICATION METHODS FOR PARKING LOT SCENARIO

Method	Accuracy	Precision	Recall	F1-score
SVM	91.8%	90.9%	92.9%	0.919
SVM - Noise Augmentation	93.9%	93.3%	95.0%	0.940
CNN	81.8%	83.8%	78.9%	0.806
CNN - Noise Augmentation	89.4%	96.7%	81.6%	0.885
CNN + LSTM	81.8%	79.6%	87.1%	0.827
CNN + LSTM - Noise Augmentation	86.1%	82.4%	93.1%	0.869
DNN	81.1%	80.5%	82.1%	0.813
DNN - Noise Augmentation	94.5%	97.2%	93.3%	0.952
DNN + TL	92.8%	97.4%	88.0%	0.924
DNN + TL - Noise Augmentation	**97.1%**	**98.5%**	**95.6%**	**0.970**

Reference of ML-based methods: SVM [19], CNN [21] and CNN+LSTM [24].

methods would not exceed 92.3% (CNN) in the corridor and can be even lower in the parking lot to 81.8% (CNN and CNN+LSTM) except for the SVM model. As for recall rate, it can indicate the capability of finding all NLOS, which in most cases is below the accuracy. SVM and CNN (for corridor only, which can be considered as an occasional case) can attain a relatively high recall rate. Given multiple scenarios and a lack of data, most existing ML-based cannot reach the desired performance.

As we proposed, the results demonstrate that it is effective to introduce data augmentation via white Gaussian noise injection for most ML-based NLOS classifiers. Among all, DNN models gain the greatest improvements in accuracy and recall rate due to data augmentation. Furthermore, it is observed that transfer learning can be helpful for multiple scenario applications but with its recall rate dropping. Thus, the proposed method deploying both data augmentation and transfer learning for a DNN model contributes to the best metrics shown in Table III and IV. For NLOS identification in the corridor, accuracy is raised by at least 2.3% (compared to CNN+LSTM), precision by 1.6% (compared to CNN+LSTM) and recall rate by at least 0.9% (compared to CNN). For the parking lot, as other ML-based methods cannot perform well in terms of accuracy, the accuracy can be increased by 5.3% (compared to SVM), precision by 1.8% (compared to CNN) and recall by 0.6% and 2.3% (compared to SVM and CNN+LSTM). In conclusion, targeting the case of multiple environments with small datasets, our proposed approach is more effective than existing techniques for NLOS identification.

E. Computational Complexity Analysis

The analysis of the time complexity of the proposed method compared with other typical ML-based methods for NLOS identification is presented in Table V. As a lightweight ML tool, the time complexity of SVM implemented by scikit-learn only depends on the input data dimension and size of the training set [46], and it consumes the least time for training and testing. With higher time consumption, deep learning methods consist of a large number of neurons and parameters to be

TABLE V
COMPUTATIONAL COMPLEXITY ANALYSIS

ML Methods	Training Time Complexity	Num of Parameters	Epoch	Train Time (s)	Test Time (s)
SVM	$O(dN^2)$	-	-	0.003	0.001
CNN	$O(NI\sum_{l=1}^{L} k_l f_l d_l)$	118210	800	195.904	0.640
CNN + LSTM	$O(NI(\sum_{l=1}^{L}(k_l f_l d_l) + w))$	32450	500	319.856	0.947
DNN	$O(NI\sum_{l=1}^{L} n_l n_{l-1})$	94210	50	17.767	0.186
DNN + TL	$O(NI(\sum_{l=1}^{L_{pre}+L_{tr}} n_l n_{l-1}))$	160260	100	44.870	0.330

L: number of layers (L_{pre} and L_{tr} are the number of layers for pre-training and fine-tuning, respectively).
d: dimension of the input (d_l is the dimension of the input of the lth layer).
N: number of the training sets.
I: number of iterations (epochs).
k_l: kernel size of the lth layer.
f_l: number of filters of the lth layer.
n_l: number of nodes of the lth layer (n_0 is the input dimension).
w: weight of LSTM.

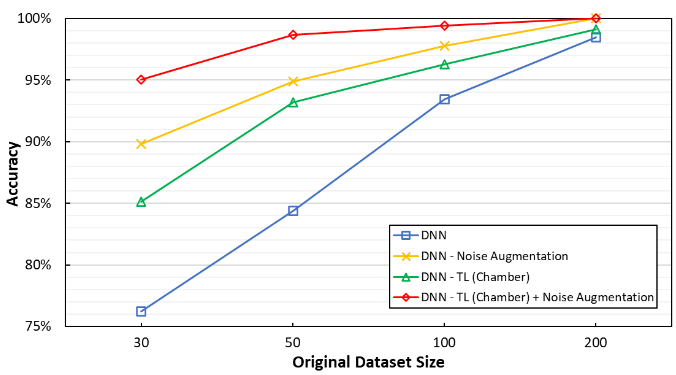

Fig. 12. Identification accuracy against training set size of DNN applied in the corridor. (TL: transfer learning)

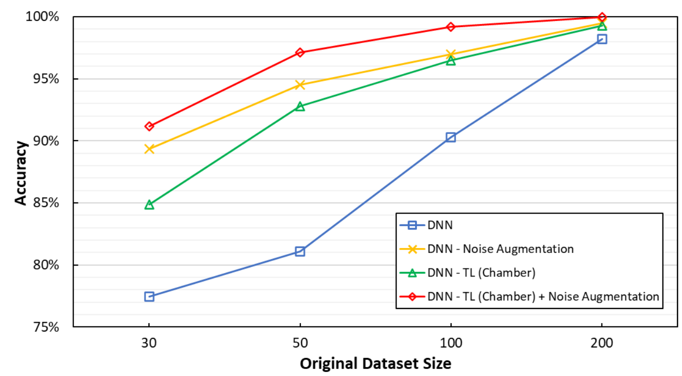

Fig. 13. Identification accuracy against training set size of DNN applied in the parking lot. (TL: transfer learning)

trained. The time complexity of CNN [21] and CNN+LSTM [24] methods are given by kernel size, the number of filters and weight (for LSTM) defined in the network [47] - [49]. Although introducing the LSTM structure can simplify the number of parameters in the network, CNN-based methods still require hundreds of iterations and high training time. As for DNN, its complexity is dependent on the number of nodes designed in its network. Similarly, the DNN classifier is complicated in terms of the number of parameters and its complexity depends on the number of nodes in the network [50], [51], but the epochs required to reach convergence largely reduce compared to CNN. Besides, applying transfer learning adds some time complexity for fine-tuning. To sum up, at a cost of time complexity, deep learning models could gain better performance. Within the tested models, the proposed method (DNN+TL), not only takes a relatively short time to train (44.9s) but also gets outstanding NLOS identification performance as discussed in the metrics comparison section.

F. Impact of Training Set Size

It is known that the size of the training set is a significant factor in the performance of a DNN model. Hence, with various training set sizes from 30 to 200, Fig. 12 and 13 demonstrate the increase in the accuracy of the proposed generalization method, compared to the basic DNN as well as DNN with transfer learning or data augmentation, individually. Based on the results, given the lack of training data from testing scenes in the corridor or parking lot, for example, when a training set size is not larger than 50, the DNN model cannot precisely classify NLOS signals with an accuracy below 90% or even 80%. For models trained by a sufficient amount of data (i.e. 200 sets), all tested approaches could result in an acceptable NLOS identification accuracy of over 98% in testing scenes of the corridor or parking lot. However, the proposed method via data augmentation and transfer learning can allow the DNN trained by 50 sets of CIR signals to resemble that trained by 200 sets, leading to approximately 98% accuracy. It effectively boosts the accuracy in identification with the same training data.

Furthermore, although the improvements in accuracy decrease as the size of training data grows, the model generalized by the proposed method with 200 sets of data can reach 100% accuracy in the test in the corridor and parking lot. To acquire high-level accuracy in NLOS identification, an extensive amount of training data is desirable, but our approach reduces this need for training data and simplifies the generalization of the NLOS classifier to new environments.

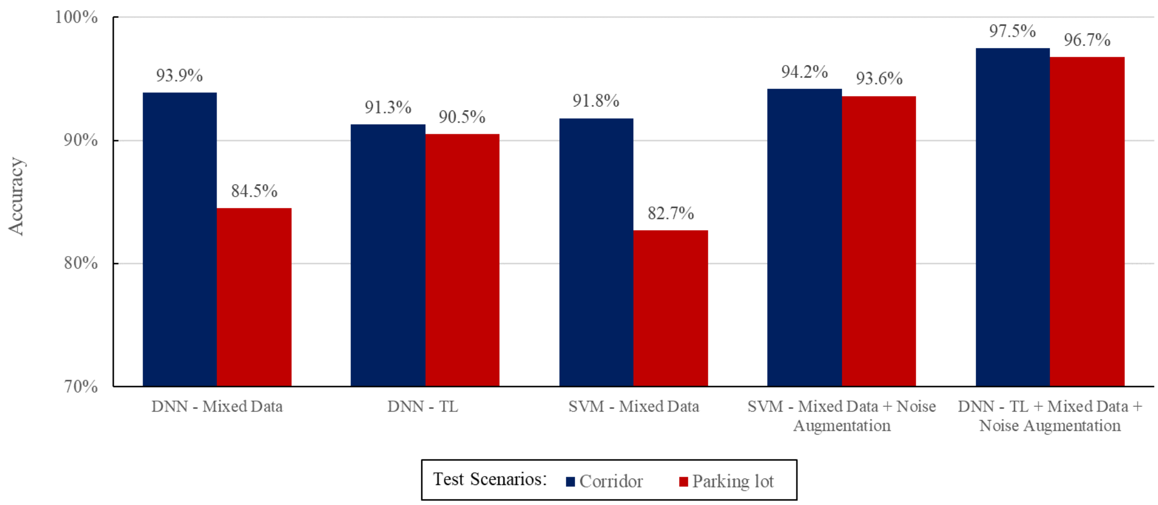

Fig. 14. Accuracy results of DNN based on a mix of 25 sets of corridor data and 25 sets of parking lot data. (TL: transfer learning)

G. Mixing Training Data from Different Scenarios

In the experiment, we also notice that data from a similar scenario is helpful for generalization and can be mixed into a dataset for training. Fig. 14 illustrates the results of models trained by a mix of CIR signals collected in different scenarios. In this experiment, transfer learning is implemented by pre-training with the same 50 sets of chamber data and fine-tuning with a mix of 25 sets from the corridor and 25 sets from the parking lot (50 sets in total). Generally, as models are trained by data collected in both scenarios, they exhibit similar and good performance in these trained scenarios, with over 90% accuracy. Compared to previous results shown in Fig. 10 and 11, there is a slight loss in accuracy when training with the mix of data from two scenarios, dropping to 97.2% and 96.7% for the corridor and parking lot, respectively (98.8% and 97.1% in comparison). The penalty is acceptable as it reveals the possibility that the data from a previously measured scenario could be mixed with new data to train a model in a new scenario. Reusing the existing data can further reduce the need to collect new data for an unmeasured environment, allowing the DNN model to be generalized among multiple environments.

H. Robustness against Noise

Based on the proposed generalization method, as the DNN model is trained by data with noise injected (between 4dB and 12dB SNR), it gains robustness against noise with similar SNRs. Fig. 15 and 16 demonstrate the robustness by illustrating the change of identification accuracy against the SNR of the test data with the addition of white Gaussian noise. For the model trained without noise (with transfer learning only), its low accuracy is mainly due to insufficient training data, but it is also important to notice that its accuracy declines a lot with SNR from 6dB to 12dB, which indicates its robustness is weak. As a comparison, with noise augmentation during training, the curves of identification accuracy in the corridor and parking lot are flatter within 6dB and 12dB, with the accuracy metric maintaining higher than 90%. It indicates that

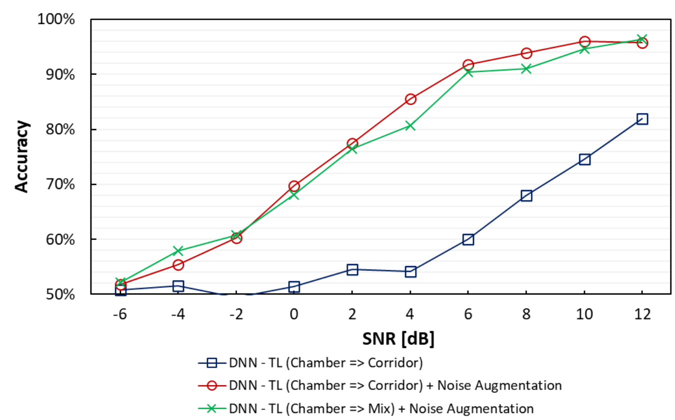

Fig. 15. Identification accuracy in the corridor against SNR of CIR based on 50 sets of training data. (TL: transfer learning)

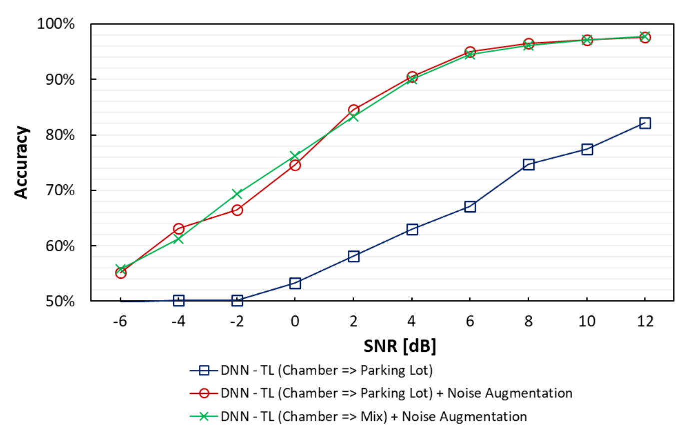

Fig. 16. Identification accuracy in the parking lot against SNR of CIR based on 50 sets of training data. (TL: transfer learning)

the model trained by our method has immunity to the noise and can be applied in some harsh cases with the SNR of signals not lower than 4dB to 6dB. For SNR below 0dB, the accuracy of most models is low as the noise power is greater than the signal power, and therefore such a noisy condition should be avoided.

I. Discussion

Deep learning models like DNN are powerful tools for classification with large neuron networks, but they require a large amount of data to train for the desired performance. Considering NLOS identification in new scenarios, it may not be possible to collect sufficient training data due to constraints such as time, materials, and risks. And using a small dataset for training may result in a model that is unable to extract the appropriate features for classification, thus yielding low accuracy. We propose a small-sample generalization method for a lab-based model via transfer learning and data augmentation to solve this problem. It is demonstrated by the results of the proposed method that based on the lab-to-real-world transfer scheme, the pre-training dataset collected with artificial LOS and NLOS setups in the anechoic chamber contributes to the improvements in the classification performance. As an enormous number of signals for a well-trained initial model can be easily measured, the need for natural signals by actual measurement is considerably reduced. It is also possible to reuse the data from other scenarios to compensate for the lack of training set. Besides, throughout the literature, applying noise jitters CIRs to assist NLOS identification has never been explored. In this paper, the experiment results prove that random Gaussian noise with controlled SNR added to CIR would not distort crucial features related to NLOS in the signal and degrade the training fitting of the DNN model. On the contrary, some advantages are demonstrated for the first time in NLOS identification on UWB CIRs, including improving generalization in multiple scenarios, complementing small-scale datasets to deal with underfitting in training, and enhancing robustness.

In fact, the original measured CIRs could include certain noise components from the environment. The injected noise may imitate the environmental noise in CIRs and the superposition of noise may cancel out part of the noise as well. Then, part of the features relevant to environments could be removed while features related to NLOS remain and could be easily extracted. It could be the reason why noise injection for data augmentation is able to effectively augment data to train a model to distinguish NLOS signals with improved performance.

Our initial expectation was that the additional Gaussian noise could act the same as an environmental effect during training for the lab-based model transfer, so no new training data is needed for generalization towards NLOS classification in multiple scenes. We then noticed that this type of noise is only partially effective and can largely reduce the required amount of training data, but data collection in a new scenario is still a must. Future studies could focus on the design of noise for CIR data augmentation so that the irrelevant features due to environmental impact could be eliminated during training.

V. Conclusion

This paper proposes a generalization method that only demands a small-scale dataset to realize DNN-based NLOS identification in multiple scenarios to assist indoor localization. Without a large amount of data for training a model, high identification accuracy for arbitrary new environments can be achieved by the cooperation of transfer learning and data augmentation. As proposed, the model is pre-trained and fine-tuned based on transfer learning, with the data from an experimental lab environment and augmented data via noise injection from a small amount of data measured in a new scenario. This method overcomes the lack of data and makes NLOS classification become available in real-world environments where measuring a large amount of data is not possible.

By testing the proposed method in a corridor and parking lot, we verify its advantages of improving accuracy in training with a small dataset, increasing from 84.4% to 98.8% and from 81.1% to 97.1% in two testing scenarios with only 50 sets of CIR signals, respectively. Hence, the results demonstrate our NLOS identification technique is effective for TOF-based indoor localization systems and related indoor automatic guided vehicles to avoid distance errors. Furthermore, the potential of lab-to-real-world transfer and data augmentation in NLOS identification with UWB CIRs is verified, offering a new opportunity to address the challenge of training data collection.

As a consequence, the experimental result manifests the powerful generalization capability and robustness of our proposed generalization method for DNN, which can become a breakthrough in the practical deployment of the multi-scenario NLOS identification approach.

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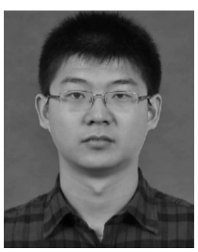

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