GAN-based Data Augmentation for UWB NLOS Identification Using Machine Learning

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Abstract— Indoor position system based on ultra-wideband technology was recognized recently as its great potential to guarantee accurate localization. Non-line-of-sight identification attracts lots of attention. Extracted from the different characters of channel impulse response using Machine Learning is proposed to reduce the localization error, caused by non-line-of-sight condition. In this paper, we proposed an efficient method using Generative Adversarial Network for data augmentation cooperating with autoencoder for enhancing the training model. The results show our framework obtained state-of-art identification performance.

Keywords— ultra-wideband, generative adversarial network, non-light-of-sight, machine learning

I. Introduction

Ultra-wideband (UWB) communication recently is one of the most outstanding technologies because of its low-power consumption, high accuracy, robust operation, and low complexity for building accurate Indoor Positioning System (IPS). However, obstacles and other interferers can lead to non-line-of-sight (NLOS) situations between the emitter and the receiver as well as decreasing the ultimate location in indoor environment [1]. Therefore, NLOS detection is important to improve the overall performance of UWB-based systems by excluding or correcting NLOS contaminated distance before employing range estimation.

There are a lot of methods are discussed for NLOS identification. These methods can be classified into four groups. In the first method, they try to find the differences of the estimated distance information under Light-of-Sight (LOS) or NLOS conditions based on a detection threshold determined by mean values of Gaussian distribution for each situation respectively [2]. The second method use the energy of the first path is dramatically greater than the energy of the delayed paths in channel impulse response (CIR) [3]. However, many factors influence the signal propagation path loss model, and manually picked features may not be sufficient for LOS/NLOS classification. The third method is built based on the context awareness of the mobile user or environment data (e.g., geometries and attenuation factors) [4]. However, this method requires large computation and also a prior position is necessary. Inspired by the superior performance of machine learning method for data classification and tackle the imbalance samples problem in NLOS and LOS dataset, we proposed a novel UWB NLOS detection and classification method based on Generative Adversarial Network (GAN) and improved Machine Learning (ML) using Autoencoder network which demonstrate the enhancement of detection accuracy. The remainder of the paper is organized as follows. Section II presents the NLOS problem and CIR model; Then, we describe imbalance data issues and data augmentation method to tackle this issue in Section III; Section IV provides detail of our frameworks; we also detail the experimental result and comparison with others method, some discussion and future works are given.

II. LOS/NLOS Problem Statement

Distance information from various channels is used to determine location results in UWB-based IPS. The Time of Arrival (TOA) method is used in UWB-based IPS for distance calculation because it provides more accurate. Meanwhile, the CIR measurements are used to obtain distance information by using the TOA technique. Figure 1 shows the CIRs of single preamble pulse generated by the LOS and NLOS signal. As can be observed, the magnitude of the LOS is substantially larger than that of the NLOS, and the curves are different. The CIR can be regarded as time series while the NLOS and LOS CIRs differ owing to the differing transmission pathways. Indeed, the NLOS reception affects the CIR curves heavily. By using machine learning methods, we can employ to deal with NLOS/LOS classification directly utilizing the CIR as the input vector.

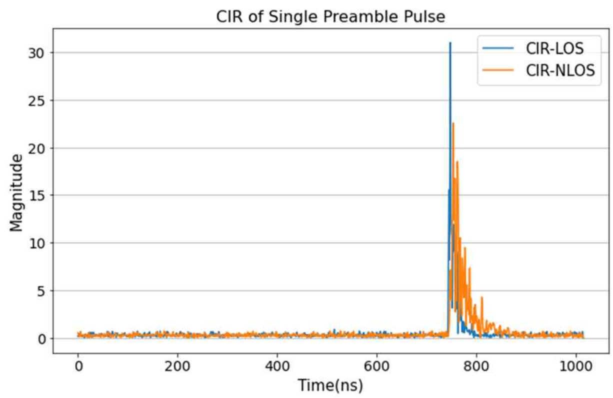

Figure 1: CIRs under LOS and NLOS condition

III. Data augmentation method

Data imbalance is one of the main challenges of LOS/NLOS classification in UWB systems. Suffering from the data imbalance problem, various ML-based methods cannot correctly identify NLOS from minority classes. Thus, reducing the interference of the imbalanced dataset to improve detection accuracy in UWB-based IPS is also a fundamental issue. In practice, the works of data augmentation in the time-series region are very limited and mostly focus on the traditional data transformation methods such as jittering, scaling, window slicing, and flipping and do not significantly improve the accuracy of the model [5]. The most popular generative method in data augmentation is the generative adversarial network (GAN) [6]. The GAN algorithm is mostly applied in image processing and image generation and recently it also provides ability to increase performance in time series data. In this paper, we generate the NLOS signal to solve imbalance data issues. Using different approaches in both the experiment and test, we evaluated the generated data comprehensively and avoided misjudging during the data generation process for obtaining the final results.

IV. PROPOSED FRAMEWORD

In general, data augmentation is mostly used in image processing because it is easy to evaluate whether the generated data is similar to the original data based on the judgement of human. Moreover, much recent research proposed simple model ML with low accuracy in training or the use Deep Learning with high complex but still not archive high performance. In our framework, we proposed training and testing process using both generated data by GAN and real data shown in Figure 2. We introduce an adaptive update strategy for Machine learning model with the Autoencoder network, so that the encoder as a data preparation step when training a machine learning improve detection model.

In practical, we introduce data augmentation using GAN to generate NLOS data similar to the original data. With different approaches and AI models, we can guarantee the evaluation process with high accuracy and similarity with the original data, which can help to improve the predictive model.

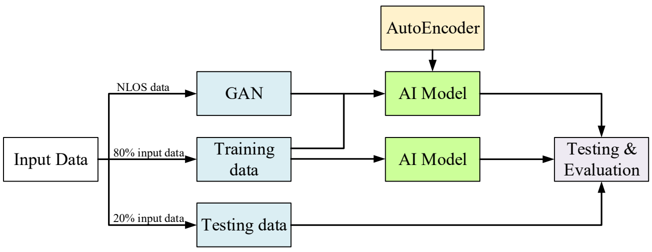

Figure 2. Training process using both real data and generated data by GAN

A. *Machine learning model and Deep Autoencoder*

The ML models analyzed in this study are Logistic Regression (LR) [7], Random Forests [8], Support Vector Machines (SVM) [9] and XGBoost Classifier [10]. These models have proved to be robust for classification applications. Moreover, these methods are very flexible when deal with different data types and structures. However, these model unoptimized in most of recently research on LOS and NLOS classification. Thus, we propose the framework using the encoder in Autoencoder network to perform feature extraction on raw CIR data that can be used to prepare input data before train and evaluate with different machine learning models.

Firstly, we provide an autoencoder network to learn compressed representation of raw data. In this scheme, the encoder compresses the input, and the decoder attempts to regenerate the input from the compressed data provided by encoder. Then, we only use encoder for feature extraction on raw data and it can be as a feature vector in a supervised learning model, for visualization, or more generally for dimensionality reduction. Figure 3 shows the loss function of the autoencoder framework while Table I summarizes the model training

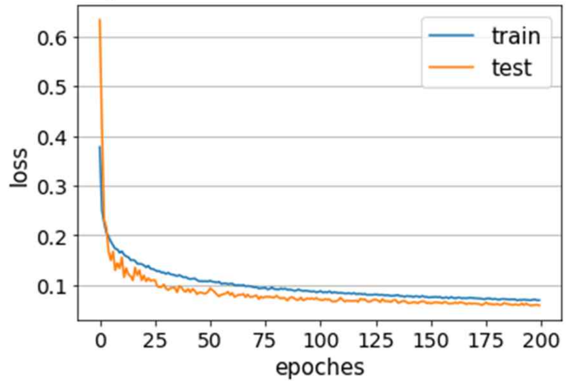

Figure 3. The Autoencoder loss

	Layer (type)	Output Shape
Encoder	Input Layer	[(None, 1016)]
	Dense	(None, 2032)
	Batch Normalization	(None, 2032)
	Leaky ReLU	(None, 2032)
	Dense	(None, 1016)
	Batch Normalization	(None, 1016)
	Leaky ReLU	(None, 1016)
	Dense	(None, 1016)
Decoder	Dense	(None, 1016)
	Batch Normalization	(None, 1016)
	Leaky ReLU	(None, 1016)
	Dense	(None, 2032)
	Batch Normalization	(None, 2032)
	Leaky ReLU	(None, 2032)
	Dense	(None, 1016)

Table I. Model Architecture for Feature Extraction

B. *GAN*

GAN is a technique designed by Ian Goodfellow [6] to generate new data from a fixed training data set. In this technique, the discriminative and the generative neural networks compete in a zero-sum game to improve themselves. Using a limited training set, the GAN techniques learn by themselves to generate data using the specific structure [11]. The most well-known GAN applications are those in computer vision, in which a photograph set is trained to generate new output with realistic characteristics for human observers.

The adversarial procedure is illustrated in Figure 3. Most existing GANs perform a similar adversarial procedure in different adversarial objective functions. In this paper, the GAN algorithm is used to generate the NLOS data signal; therefore, only NLOS data is fed into the generator. The generator generates the NLOS data using random noise, which ranges from 0 to 1 with normal distribution to guarantee the difference in the output data. Meanwhile, the discriminator distinguishes the generated samples and the data samples. Given adequate capacity and training time, the generative neural network and the discriminator network will converge and achieve a point where the generator produces samples so real that make the discriminator cannot distinguish them from the real data.

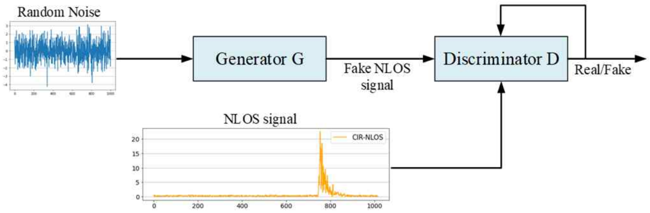

Figure 4. GAN model for NLOS data augmentation

C. Data Generating

The preprocessing procedure for the generated signal is the same as that for the original signal, and, based on that, we can evaluate its quality using previous LOS/NLOS detection methods. Note that we generate the signal only for the NLOS signal because this signal is assumed to be less than the signal obtained for the original data.

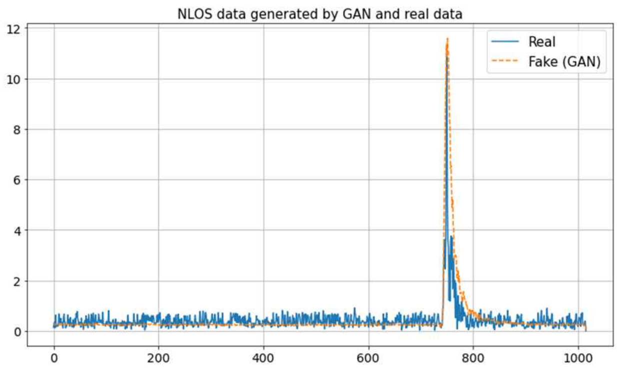

Figure 5. Data Generation using GAN

In our proposed framework, we trained 500 sample NLOS using GAN with noise dimension was 32 and 1016 features CIR respectively with real input data. After completing the generation, we provided these synthetic sample for training dataset and execute ML model for classification. The results archived from our proposed framework was presented in subsection IV.D.

D. Classification Accuracy Comparison

After selecting approximate Autoencoder model, this subsection aimed to evaluate these ML model with our proposed framework. Autoencoder and ML consisted of LR, RF, SVM and XGBoost were deployed to classify the NLOS/LOS in UWB-based IPS. Besides, we generated NLOS data for solve imbalance issues using GAN which described as subsection IV.B. For comparing these methods fairly, they were incorporated with the parameter. Dataset for training and testing were the same as that described in Figure 2.

For evaluation of our algorithm in various conditions, we utilized a dataset from different locations described in [12]. Specifically, the dataset was created by SNPN-UWB board with DWM1000 UWB radio module in seven different indoor locations. After applying the original model with two scenarios: (1) comparison among different locations and (2) comparison among different ranging distances, we perform k-fold cross validation with k=10. The result according to Figure 6 show that XGBoost has a higher value of average detection accuracy than other traditional methods for all location . The high performance of XGBoost has been achieved thanks to the optimization of this algorithm. Besides, these results imply that different contexts have an impact on UWB signal quality, causing signal classification to be inconsistent under LOS and NLOS conditions. ML algorithms still perform well at NLOS/LOS classification as indicated by the fact that the accuracy is still relatively good, averaging 80% and higher. To enhance the traditional ML, we also use the encoder layer from Autoencoder model which was defined in Table I. For instance, the accuracy of SVM support with encoder layer increased more than the original one from 2-3% due to extracting important feature of signal before putting data into SVM model. Figure 6 also shows this advanced SVM has the most efficient detection accuracy compared to the other algorithms. However, the result still not be improved with lower ranging because of imbalance issue.

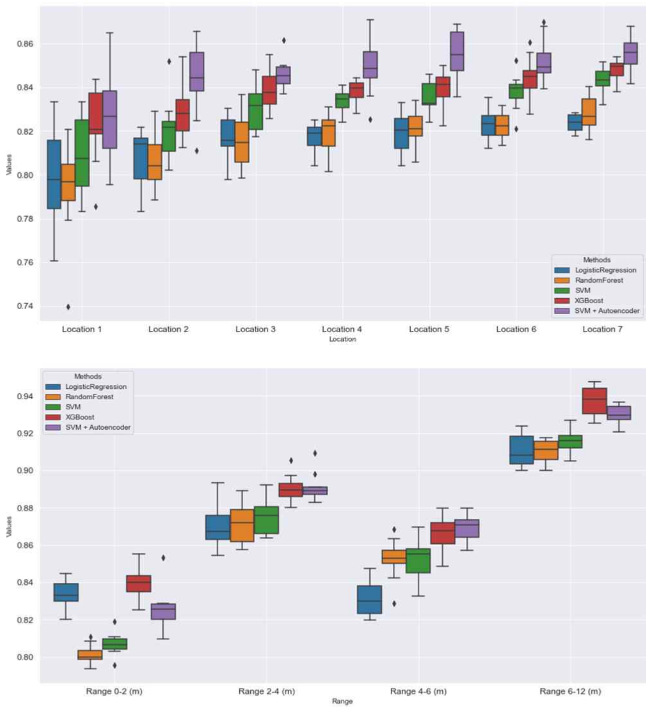

Figure 6. Accuracy of NLOS detection based on ML

We deployed our model with the ranging distance from 0 to 2m which we applied GAN for data augmentation before evaluating the NLOS identification models. The classification accuracy comparison results were listed in the Table II. In without GAN scenario, we archived 79.92% to 83.58% based on LR, RF, SVM and XGBoost method. Specifically, XGBoost show the highest accuracy when identifying NLOS signal. After applying encoder layer, we got accuracy up to 82.25% with LF and 83.67% with SVM, that imply the improvement of classification accuracy when we deploy Autoencoder for transform input data before training model. Moreover, with data augmentation by using GAN, ML model perform more accurate than that without GAN. These results show that our proposed GAN can solve data imbalance and it can reach the accuracy of ML up to 86.98%. Specifically, SVM performed the best result for NLOS identification compare with another ML which supported by encoder processing and GAN.

Data augmentation is useful in the training process when the number of NLOS samples is so small that the model cannot be trained effectively. This characteristic is very suitable in NLOS detection in UWB-based IPS because of the lack of NLOS signal at the start of the implementation phase. With the improvement of GAN, we can generate NLOS data for applying the classification with high similarity to the original data. Using various experiments and evaluations, we can conclude that the generated data has a high similarity with the original data in both the time domain and frequency domain. The generation data significantly improved the application of training performance with a large CIR samples in UWB-based IPS. Although we could generate high-quality input data, the original NLOS data are also necessary for testing and partial training.

	Method	Accuracy (%)
No-GAN	Logistic Regression	79.92
	Random Forests	80.42
	Support Vector Machines	82.00
	XGBoost Classifiers	83.58
	RF + Autoencoder	82.25
	SVM + Autoencoder	83.67
GAN	Logistic Regression	82.58
	Random Forests	81.45
	Support Vector Machines	85.12
	XGBoost Classifiers	86.67
	RF + Autoencoder	83.33
	SVM + Autoencoder	86.98

Table II. Model Architecture for Feature Extraction

V. CONCLUSIONS

This study proposed a novel method to generate the NLOS signal data, thus enhancing NLOS identification accuracy in the case of a limited dataset for training. After testing, we conclude that the generated data has high similarity to the original data and significantly improves the accuracy of the model with limited real NLOS data in the training dataset.

However, the data augmentation method using GAN still has a limitation, since the high variety can reduce the output signal and unstable during the training process. Therefore, the architectures of both the generator and discriminator should be considered carefully, and the output of GAN has to be carefully evaluated. With these remain challenges, we consider providing other generative AI models for the data augmentation and compare with the current scheme.

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