A Novel CNN Model for NLoS Classification in UWB Indoor Positioning System

Mohammadali Ghaemifar*
Department of Electrical Engineering
Iran University of Science and Technology
Tehran, Iran
m_ghaemifar@elec.iust.ac.ir

Saeed Ebadollahi
Department of Electrical Engineering
Iran University of Science and Technology
Tehran, Iran
s_ebadollahi@iust.ac.ir

Milad Ghasemzadeh
Department of Electrical Engineering
Iran University of Science and Technology
Tehran, Iran
milad_ghasemzadeh@elec.iust.ac.ir

Saba Pirahmadian
Department of Electrical Engineering
Iran University of Science and Technology
Tehran, Iran
saba_pirahmadian@elec.iust.ac.ir

***Abstract*— According to the research conducted, people spend about 70-90% of their living and working time indoors. Therefore, providing systems that offer adequate services to users in these environments seems essential. Locating users and devices is widely used in healthcare, industry, building management, surveillance, and other areas. There are various technologies for indoor positioning systems. In this paper, Ultra Wide Band (UWB) technology is considered due to its high accuracy in indoor positioning. However, there are many objects and people in indoor environments, so obstacles can reflect the transmitted signals. Compared to the Line of Sight (LoS) signal, the delay of the signal transmission path in the Non-Line of Sight (NLoS) signal leads to positive range errors.**

In order to reduce the effect of NLoS conditions on positioning. In this research, we have attempted to achieve high-precision accuracy separation for LoS and NLoS conditions by providing deep learning networks and using channel impulse response data as input without prior knowledge of the environment. In addition, the result of this classification is compared to other references that used a similar dataset. The results of the NLoS/LoS signal classification section show that the proposed Convolutional Neural Networks (CNN) are better than other neural network methods (such as Deep neural networks).

Keywords*— *Internet of Things, Indoor Positioning Systems, UWB, NLoS Classification, Deep Learning, CNN

I. Introduction

While the Internet of Things (IoT) connects things and gathers data, indoor spaces often lack precise location tracking. This is where Indoor Positioning Systems (IPS) come in, complementing IoT by providing accurate indoor location data, which is crucial for context-aware services within buildings. Positioning is the process of determining the location of people, devices, and other objects, which has been a very active area of research in recent years. Most of the research in positioning has focused on using existing technologies to overcome the challenge of positioning. Depending on the environment in which positioning takes place, positioning can be divided into two groups: outdoor positioning and indoor positioning. There are different positioning technologies depending on the type of environment. GPS, for instance, is an efficient and suitable technology for outdoor areas; however, it is not suitable for indoor environments, as satellite signals cannot pass through obstacles and walls. Therefore, the GPS is not very practical, which has led to the development of indoor positioning systems.

IPS is a type of local positioning system that enables positioning to locate people or objects within a building. The Global Navigation Satellite System (GNSS) has played an important role in providing accurate location information [1]. However, it is not an ideal solution for indoor positioning due to its inability to provide accurate indoor positioning [2]. Over the past decades, extensive studies have been conducted on indoor device localization, and the use of IPS has increased. Nowadays, indoor positioning systems are widely used in the Internet of Things [3], smart buildings [4], smartphones[5], Unmanned Ground Vehicle (UGV) navigation [6], etc.

There are various technologies for indoor positioning systems. These are based on wireless technologies such as Bluetooth, Zigbee, WiFi, Radio Frequency Identification (RFID), Ultra-Wideband (UWB), etc., each of which can be implemented with different algorithms and techniques that are used specifically for indoor positioning. UWB technology is very suitable for situations where high accuracy is important. The accuracy of positioning with this technology reaches the centimeter range. It can be improved by methods such as the Kalman filter [7], the combination of two technologies [8], antenna calibration [9], the weighted centroid point estimation algorithm [10], etc.

However, the practical use of UWB systems still faces several technical challenges, including signal reception, multi-user interference [11], multipath effects [12], and NLoS propagation. NLoS leads to positively biased range estimates, and without the detection of NLoS signals, the positioning accuracy decreases [13]. In recent years, Deep Learning (DL) algorithms have achieved success in indoor localization [14]. The main advantage of machine learning and deep learning approaches is their ability to make effective decisions based on observational data without precise mathematical formulation.

This research addresses the challenge of NLOS conditions degrading positioning accuracy. We propose a deep learning based approach that leverages Channel Impulse Response (CIR) data as input to achieve high-precision separation of LOS and NLOS conditions. Notably, this method does not require prior knowledge of the environment, making it adaptable to various deployment scenarios.

The rest of the paper is organized as follows: A Discussion on the NLoS detection methods is Presented in Section II. A brief overview of DL techniques It is presented in Section III. In section IV, we verify the performance of our proposed novel CNN model through simulations, comparing it to other papers. Section V then draws conclusions based on the verification results.

II. NLoS Detection Methods

In IPS-based UWB technology, NLoS detection is very important to obtain clean distance information. NLoS detection is the entry point to improve positioning accuracy, and many approaches have been presented in previous articles to solve this problem. For example, CNN's method has achieved a positioning accuracy of 18 cm without considering NLoS conditions [15], but the same paper has identified NLoS and reduced its impact. These conditions have achieved an accuracy of 12 cm, which is a 6 cm improvement in accuracy. In general, these methods can be categorized into the following three types.

The first method is Statistical Analysis. This method leverages the differences in statistical properties of estimated distance information between LoS and NLoS conditions [16]. The second one is based on the signal propagation. This approach utilizes the signal propagation model or CIR to identify the dominant presence of a strong first path, typically observed in LoS conditions [17]. Finally, the third case is the use of the machine learning method. This method employs parameter-free algorithms, such as Support Vector Machine (SVM), Multi-Layer Perception (MLP), or Decision Tree (DT), to learn and classify LoS/NLOS conditions based on extracted features.

With IPS-based UWB technology, distance information is obtained from various channels to calculate the location data. Since the Time of Arrival (ToA) method has the advantage of high accuracy, it is used in UWB technology. In the ToA method, the distance information is extracted from the Channel Impulse Response (CIR) measurements [18]. From the measurements in the articles, it can be concluded that the CIR is different for the two environments, LoS and NLoS, and it can be seen that the CIR in the LoS environment is larger than that in the NLoS environment. The curves of these two environments are also different from each other. DL methods such as CNN can be used for the classification of NLoS/LoS conditions by using the CIR as a network's input.

III. Model Design

In this section, we start by giving an overview of classification in Deep Learning. Then, we explain the new CNN model and its design details. Finally, we summarize the structure of our proposed network. Finally, we provide insights into the dataset used for our study.

A. *Deep Learning Classification Overview*

Classification algorithms are a fundamental part of learning that focuses on categorizing data into predefined groups. This branch attempts to train models that automatically assign labels to input data based on patterns and features extracted during the learning process. Classification algorithms in deep learning use multi-layer neural networks that allow the system to learn complex hierarchical representations of data. These algorithms are very powerful in processing huge amounts of unstructured data and provide accurate predictions and classifications.

By using techniques such as CNN, Recurrent Neural Networks (RNN), and more advanced architectures, complex features can be learned from raw data, leading to outstanding performance on various classification tasks through forward and backward propagation iterations. Deep learning classification algorithms optimize their parameters to reduce errors and increase accuracy when classifying data into different categories.

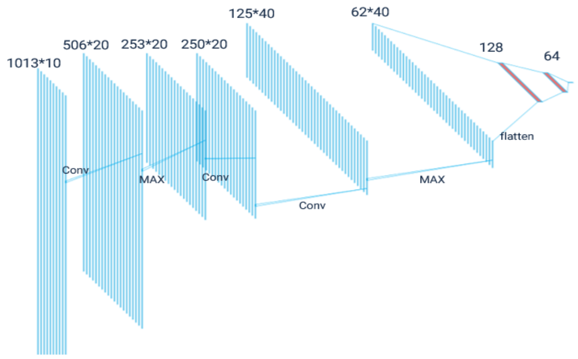

Fig. 1. Proposed CNN Architecture

In Convolutional Neural Networks (CNNs), each layer comprises individual processing units, or neurons, that analyze specific portions of the input data. These neurons are grouped based on shared weights, enabling them to detect the same features within the input efficiently. Each group generates a "feature map," summarizing its findings for further processing in the subsequent layer.

B. *Novel CNN Architecture*

The activation function chosen for all neurons in this CNN architecture is the Rectified Linear Unit (ReLU) function. ReLU offers a suitable level of non-linearity while remaining computationally efficient. Additionally, it maintains the network's performance compared to more complex alternatives like Sigmoid or Tanh. Another key layer type is the pooling layer, which utilizes a sampling technique to decrease the influence of features extracted from the previous layer's output. Notably, this architecture employs max-pooling, which selects the maximum value from specific data windows and feeds it forward. These windows, characterized by their size and stride, enable dimensionality reduction. For instance, a pooling window of size 2 and stride 2 selects two input values and moves by two, leading to a 50% reduction in the input dimensions.

TABLE I. DETAILS OF PROPOSED CNN ARCHITECTURE

Layer's number	Operation	Size of filter	Number of filters	Output size	activation	padding	strides
1	Convolution	4	10	1013×10	ReLU	valid	1
2	Convolution	5	20	506×20	ReLU	same	2
3	MaxPooling	2	20	253×20	-	valid	1
4	Convolution	4	20	250×20	ReLU	valid	1
5	Convolution	4	40	125×40	ReLU	same	2
6	MaxPooling	2	40	62×40	-	valid	1
7	Fully Connected	128	-	128×1	ReLU	-	-
8	Fully Connected	64	-	64×1	ReLU	-	-

After the steps of convolution and pooling layers, the fully linked double layer is applied as the last step. These two layers, which are a combination of convolutional layers and dimensionality reduction layers, act as a kind of automatic preprocessing for the inputs, which is used instead of traditional methods for extracting features from the data. These layers have the task of automatically extracting features for the fully connected neural layer. The fully connected layer contains all neurons with all outputs of the last convolutional layer. Finally, in the output layer, the binary output is determined and obtained using a sigmoid or softmax activation function. The novel model structure of a CNN is shown in Fig. 1. Also, the details of the parameter values of the proposed network, including the active function, the number of neurons, filter, etc., can be comprehensively seen in Table I.

C. Dataset

The measurements were performed using DW1000 UWB transceivers connected to a Raspberry Pi network computer using the SNPN_UWB internal radio board, following the methodology established by researchers in [18]. This measurements were taken in four different indoor environments. In each environment, there are 119040 measurements and eight anchors, so 14880 samples were taken for one anchor. In this research, as it mentioned, the aim is to separate NLoS/LoS conditions without any prior knowledge of the environment. For this purpose, we use the CIR feature recorded in this dataset.

CIRs are a fundamental concept in communications and signal processing that describes how a signal is transmitted through a communication channel. It can be said to be a kind of mathematical function that represents the response of the channel to a short pulse or impulse. Here, 1016 samples of the channel impulse response were taken. The CIR0-CIR1015 values listed in the dataset represent the amplitude and phase of the channel response at 1016 different time instants.

CIRs can be seen in Fig. 2. for two randomly measured samples of the channel impulse response in NLoS and LoS conditions. The amplitude value of the NLoS signal is much lower than that of the LoS signal, as expected. In other words, due to the presence of an obstacle between the transmitter and receiver, i.e., the NLOS state, a lower amplitude value is obtained at the receiver. It should be noted that it is not possible to tell whether the signal is LoS or NLoS simply from the CIRs because one of the reasons for the low amplitude should be the distance between the receiver and the transmitter.

IV. RESULTS

In this section, the results presented were compared with two studies that used this dataset, the first in [19] that used a deep learning method called CNN-LSTM to classify LoS signals and NLoS signals that achieved 82.14% accuracy and the second in [18] recognize indoor NLoS conditions using UWB impulse response information. They proposed a method based on the classification of NLoS channels using CNN with 87.4% accuracy. The exact details of the parameter values considered for the simulation can be found in these two references. Based on the definitions and quantification of the network given in the previous section, the results of the following table can be briefly summarized. The following simulation results were used from the mentioned structure, with the difference that two values of 0.5 and 0.8 were assumed when using dropout. To carry out simulations and implement deep learning algorithms in this paper, a computer system with an Intel i7-4720HQ processor with a frequency of 2.6 GHz, a GeForce GTX 960M graphics card, and a RAM with a capacity of 8 GB is used to run the simulations and implement the deep learning algorithms.

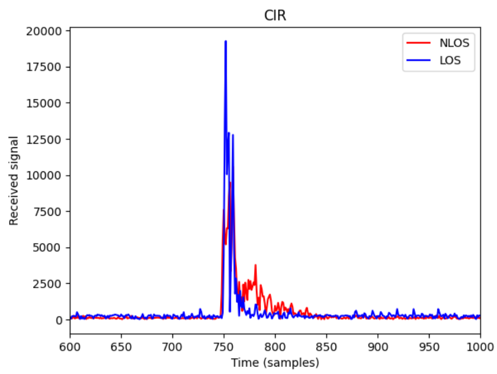

Fig. 2. Channel impulse response of NLoS/LoS conditions

A. CNN with Dropout=0.5

In the case when the value of 0.5 is used as the dropout value, we obtain the following results. According to the accuracy graph in Fig. 3, after the 20th period, the test accuracy is constant and around 92%, while the training accuracy is 95%. This is a percentage, and the difference in accuracy between these two graphs does not change further. For comparison purposes, we employed a DL neural network with three hidden layers containing 256, 128, and 64 neurons, respectively.

Each layer utilized the ReLU activation function. Another factor that we consider to analyze results is the confusion matrix. The confusion matrix in this network is also shown. The confusion matrix is a useful tool for evaluating the performance of a learning algorithm, as can be seen in Fig. 3. This matrix is a two-dimensional table in which each row represents an actual class, and each column represents a predicted class. In neural network prediction, the confusion matrix can be used to

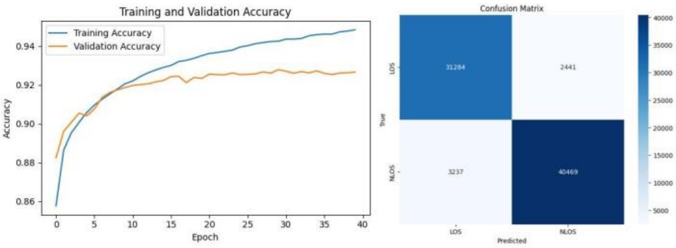

Fig. 3. Accuracy and Confusion Matrix of CNN with Dropout = 0.5

evaluate the performance of the network in classifying data samples. This matrix can provide information about the accuracy, precision, sensitivity, and specificity of the network. Each cell in the confusion matrix represents the number of samples belonging to the actual class and the predicted class. For example, the cell in the upper left corner of the matrix shows the number of samples that are in the actual class "0" and also in the predicted class "0", where class "0" is the LoS condition. The results of the confusion matrix show that 5678 test samples are not correctly predicted.

B. *CNN with Dropout=0.8*

To check the effect of the dropout and reduce the little overfitting of the previous model from the 20th period onwards, its value was changed to 0.8, and we obtained the results in Fig. 4. As can be seen, the accuracy of the test reached the same level as the accuracy of the training and is around 90%, which is less than the accuracy of the previous CNN network. The confusion matrix for this network can be seen in Fig. 4, which can be compared with the network earlier. For example, in the case of the LoS conditions, there were 2441 incorrect predictions in the previous network, But for this network, it has reached 3968 samples.

Fig. 4. Accuracy and Confusion Matrix of CNN with Dropout = 0.8

V. CONCLUSION

This study explores the application of Convolutional Neural Networks to NLoS/LoS signal classification using channel impulse response data. This classification is crucial for accurate target positioning in UWB indoor environments, where NLoS conditions can distort the signal and lead to positioning errors. To achieve high classification accuracy, we evaluated two CNN architectures with dropout values of 0.5 and 0.8. The performance of these models was compared against a Deep neural network with three hidden layers and two existing approaches that utilized a similar dataset. Our proposed CNN models achieved impressive classification accuracies of 92.67% and 90.06% for different NLoS/LoS scenarios, outperforming other methods using the same dataset. Our approach is improving the accuracy of indoor positioning systems by mitigating the detrimental effects of NLoS conditions. All results of the proposed methods are summarized in Table II.

TABLE II. RESULTS OF NLOS/LOS CLASSIFICATION

Neural networks	Training time (m)	Training accuracy %	Test accuracy %	Cost function	Execution time in real-time (ms)
CNN, Dropout 0.5	105	94.84	92.67	0.20	33.90
CNN, Dropout 0.8	97	90.16	90.06	0.24	28.92
DL Neural Network	62	93.19	88.40	0.36	19.8

VI. FUTURE WORKS

Implement separate regression networks to estimate target position under two conditions:

- Considering NLoS: This approach will use the information from NLoS classification to improve position estimation by considering the effects of signal distortion.
- Not considering NLoS: This approach serves as a baseline for comparison, allowing us to assess the improvement gained by considering NLoS conditions.

By comparing the position estimation accuracy under both conditions, we can quantify the effectiveness of NLoS classification in mitigating the negative impact of NLOS on indoor positioning systems.

Further research directions include investigating the application of transfer learning techniques to leverage knowledge gained from a specific environment (e.g., a building) to improve positioning performance in other environments. This model can be optimized for real-time implementation, considering the constraints of practical applications.

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