Design and Evaluation of CNN-Based versus Statistical, Neural Network NLOS Detection in UWB Systems

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***Abstract*—Precise distance estimation using Ultra-Wideband (UWB) for indoor localization systems is challenged by non-line-of-sight (NLOS) conditions. NLOS conditions caused by obstruction of the direct propagation path result in overestimation of the distance between sensors or erroneous angle of arrival measurements and finally result in localization errors. Therefore, reliable NLOS detection is fundamental to identify these errors and ensure robust position estimation. This work introduces a detection approach for UWB signals analyzed by a one-dimensional convolutional neural network (1D-CNN). The 1D-CNN uses the UWB received signals as input and automatically learns the relevant features, enabling more robust NLOS detection than other approaches. We compare our approach with two state-of-the-art detection algorithms: First, a statistical approach based on eight weighted features and thresholding; secondly, a feature-based neural network using the same features. This comparison provides a fair baseline for evaluating the advantages of our proposed method. We evaluate the NLOS detection performance with real measurements on a popular UWB hardware with a Decawave DW1000 chip. The effectiveness of the NLOS detection shows a 99.91% detection ratio compared to 60.81% for the statistical approach and 95.58% for the feature-based neural network approach.**

***Index Terms*—Ultra wideband, neural network, channel impulse response, statistical propagation, line-of-sight, non-line-of-sight, Non-line-of-sight Detection, 1D-CNN, DW1000.**

I. Introduction

In industrial environments, precise indoor localization of objects is important, e.g., in logistics, automation technology, and robotics. Due to its large bandwidth, Ultra-Wideband (UWB) localization suits the demand and offers good time-of-flight accuracy [1], enabling centimeter-level localization via multilateration. Accuracy can be improved further by angle of arrival measurements [2]. The problem addressed in our work is a supervised binary classification: a reliable distinction between Line-of-Sight (LOS) and Non-Line-of-Sight (NLOS) conditions for the received signal. A distinction between LOS and NLOS can improve the performance of localization significantly [3]. As shown in Figure 1, Sorrentino et al. define LOS and NLOS with the help of Fresnel zones as follows [1]:

A LOS condition exists when the first Fresnel zone is free of obstacles. The received signal contains a strong direct path as well as possible multipath components (reflections from walls or the floor). Conversely, a NLOS condition occurs when the direct path is obstructed [4]. Here the received signal consists of a weak portion of the first Fresnel zone or only of multipath components. In the NLOS case, the distance measurements of UWB might not detect the first path signal of the direct path and measure the distance based on any reflected signal. The same applies when multi-antenna systems measure the angle of arrival. This leads to erroneous position estimations [5].

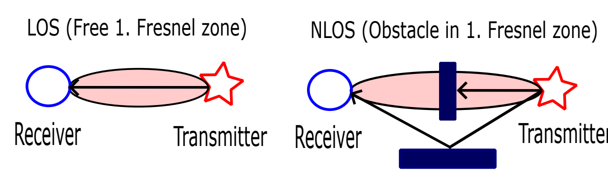

Fig. 1: Illustration of LOS and NLOS.

This work presents a comparative analysis of three NLOS detection approaches: a feature-based statistical approach, a feature-based neural network, and our new one-dimensional Convolutional Neural Network (1D-CNN), which processes the received signals directly. By applying the Decawave DW1000 chip for real-world measurements, we demonstrate the performance and practical applicability of our proposed solution. Our main contributions of this work are:

- Design of a 1D-CNN solution for NLOS detection.
- Comparative analysis of the statistical, feature-based neural network, and our CNN-based method.
- Implementation of the detection approaches for real-time systems, free for download.
- Achievement of more than 99% classification accuracy with our proposed CNN approach.

The remainder of this paper is structured as follows: Section II reviews related work on statistical, feature-based, and deep learning approaches for LOS/NLOS classification in UWB systems. Section III outlines the core concept and motivation. Section IV details the three evaluated methods, measurement setup, and preprocessing. Section V presents a comprehensive evaluation of the approaches using real-world data from the Decawave DW1000 hardware, including challenging boundary

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cases. Finally, Section VI summarizes findings, implications, and future work.

II. Related Work on NLOS detection

Existing work is categorized into three main areas: statistical and threshold-based approaches, feature-based machine learning approaches, and deep learning approaches.

Statistical approaches use features, including the amplitude of the first signal path, the total energy, or statistical parameters such as Kurtosis and Skewness of the received signal. In [6] and [3], various parameters from the signal are utilized, such as Skewness, Kurtosis, Root Mean Squared Delay Spread (RDS), and Mean Excess Delay (MED) [7]. They further improve accuracy by using the Joint Probability Density Functions (PDFs) of these parameters, with classification criteria based on the Likelihood Ratio and a Hypothesis Test. The results of this approach can achieve accuracies of over 85%, although the performance is dependent on the environment and the determined thresholds. We use these features for an analysis of this approach. Feature-based machine learning approaches, such as works from Huang et al. [8], enhance the classification of LOS and NLOS. In these approaches, statistical parameters like Kurtosis or RDS are selected as input for a neural network. Several studies compare different machine learning methods, such as Support Vector Machines (SVM) and Random Forests, with deep learning approaches like Deep Forward Neural Networks (DFNN) [9]. These approaches provide a more robust and higher accuracy. In recent years, the focus has shifted toward deep learning to handle the weaknesses of feature-based methods. Convolutional Neural Networks (CNNs) have proven to be effective, as they can learn relevant features directly from raw data, such as the received signal [10], [11]. Depending on the training and testing sets, these approaches reach an accuracy of up to 99% [9]. Our work proposes the use of a 1D-Convolutional Neural Network and uses the entire signal to optimize NLOS detection. Addressing a gap in existing papers, we introduce a simple 1D-CNN with high accuracy by learning directly from the received signals. We provide a comparison of our approach against two major method categories: a statistical and a feature-based neural network.

III. Fundamentals of NLOS Detection

A. Fresnel Zones

The definition of LOS and NLOS is best explained by the concept of Fresnel zones [12]. In contrast to the simple assumption of a straight signal beam, the signal spreads as a wave in space. The Fresnel zones are ellipsoid-shaped regions around the direct path between the transmitter and receiver. The first Fresnel zone is the most important; it contains most of the signal power. The second Fresnel zone is an area that, when fully obstructed, causes a 180° phase shift. The third Fresnel zone causes a phase shift that constructively interferes with the signal. The influence of the third-order zones and higher diminishes significantly. We consider an LOS condition as long as the first Fresnel zone is free of obstacles, and NLOS if there are obstacles in this first Fresnel zone. A LOS signal contains the main path with the whole signal from the first Fresnel zone and multipath components (MPC) such as reflections from a wall or the floor. An NLOS signal contains only MPC and just a part of the first Fresnel zone.

B. Multipath Propagation

For indoor localization, we focus on a UWB signal as motivated in the introduction. The transmitter emits a UWB transmit signal $x(t)$ of bandwidth $B \approx 499\,\mathrm{MHz}$ and center frequency $f_c = 3.9936\,\mathrm{GHz}$ [13]:

$$x(t) = \mathrm{si}(t/T_{\text{sinc}}) \cdot \cos(2\pi \cdot f_c \cdot t), \tag{1}$$

where the sinc pulse $\mathrm{si}(\cdot)$ defines the baseband signal with zero spacing $T_{\text{sinc}} = 1/B$. The cosine term shifts the spectrum to the transmission band centered at f_c. The transmit signal $x(t)$ is radiated omnidirectionally into the environment. Each path's signal echo is described by its amplitude $\underline{a_i}$, its Time of Arrival (ToA) τ_i), and experiences a 180° phase shift per reflection. At the receiver, the direct path arrives first with ToA τ_0 because it is the shortest one. The ToA is crucial for distance measurement and forms the basis for LOS conditions. In addition to the direct path, the receiver also captures signals that are reflected from walls, the floor, the ceiling, or other objects. These multipath components (MPCs) have larger propagation delays due to the increased travel distance and arrive with reduced signal strength, since energy is lost at each reflection and over longer distances. The multipath propagation of I signal echoes is modeled by the channel impulse response (CIR) $h(t)$.

$$h(t) = \sum_{i=0}^{I-1} (-1)^{n_i} \underline{a_i} \cdot \delta(t - \tau_i), \tag{2}$$

where the ToA is modeled by the Dirac function $\delta(t - \tau_i)$, the phase shift per reflection, results in a sign change $(-1)^{n_i}$. At the receiver, all echoes superpose, yielding the received signal $y(t)$ as the convolution of $x(t)$ with the CIR $h(t)$:

$$\begin{aligned} y(t) &= x(t) * h(t) && (3)\\ &= \sum_{i=0}^{I-1} (-1)^{n_i} \underline{a_i} \cdot \mathrm{si}\left(\frac{t - \tau_i}{T_{\text{sinc}}}\right) \cdot \cos(2\pi \cdot f_c \cdot (t - \tau_i)) && (4) \end{aligned}$$

Note, in NLOS conditions, the first path amplitude a_i decreases or vanishes.

C. LOS vs NLOS conditions

Figure 2 provides the measurement of a received UWB signal for a LOS condition in red and a NLOS condition (blocked direct path) in blue. The LOS signal has a dominant first signal echo followed by reflections reaching the receiver. In NLOS condition, the direct path has been blocked, missing a clear first path peak like in the LOS signal. The first path component is the most significant difference between the LOS and NLOS signals. But there are many characteristic differences also in the MPCs suitable for condition detection.

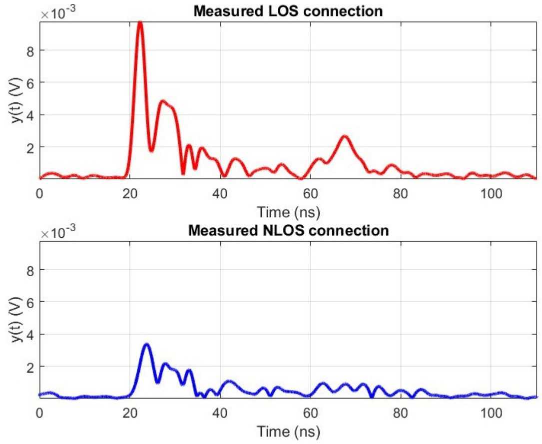


Fig. 2: LOS and NLOS signals

For example, a simple approach implemented by the DW1000 is to calculate the ratio of the First Path Power Level (FPPL) to the total received signal power (RxLevel). In the following, we include approaches that evaluate eight features for detection, either statistically or based on machine learning. We compare these with our approach: the 1D-CNN automatically extracts its own features from the received signal.

IV. Implementation

This section describes the implementation of the three NLOS detection approaches. To ensure the accessibility of our results, we offer an implementation of the approaches available for integration into real-time systems.[1].

A. Preprocessing of the Received Signals

For NLOS detection, we will focus on the signal envelope $A(t)$ of the received signal $y(t)$. For the feature-based approaches, the signal envelopes are extracted using the Hilbert transform and then used directly [14]. For the 1D-CNN approach, each envelope's sample $A[i] = A(i \cdot T_S)$ is additionally normalized per i-th sample as

$$A_{norm}[i] = \frac{A[i] - \mu(A)}{\sigma(A)}, \text{where} \tag{5}$$

$$\mu(A) = \frac{1}{I}\sum_{i=0}^{I-1} A[i] \text{ , and } \sigma(A) = \sqrt{\frac{1}{I}\sum_{i=0}^{I-1}\left(A[i] - \mu(A)\right)^2}$$

where $\mu(A)$ and $\sigma(A)$ are the mean and standard deviation of the discrete envelope $A(t)$. This normalization $A_{norm}[i]$ ensures scale invariance and stabilizes the network training.

B. Statistical Approach

The statistical approach detects the transmission condition (LOS or NLOS) from eight statistical features:

[1]https://git.mylab.th-luebeck.de/sven.ole.schmidt/mscheel-nlosdetection

Time of Arrival: The Time of Arrival (ToA) is a fundamental characteristic in UWB systems, representing the arrival time of the first detected path in the received signal. It is crucial for distance estimation, as the distance is directly proportional to it.

First Path Power Level: The First Path Power Level (FPPL) describes the signal strength of the first detected path in the received signal. This value thus provides crucial clues for distinguishing between LOS and NLOS scenarios.

Total Energy: The total energy ε_τ describes the total energy contained within the received signal. The total energy is calculated by integrating the squared magnitude of the signal $y(t)$ over time [6].

$$\varepsilon_\tau = \int_{-\infty}^{+\infty} |y(t)|^2 \, \mathrm{d}t \tag{6}$$

Energy Ratio: Besides, the energy ratio ε_r expresses the ratio of the first path energy ε_1 to the total energy ε_τ [6].

$$\varepsilon_r = \frac{\varepsilon_1}{\varepsilon_\tau} \tag{7}$$

Skewness: Skewness describes the asymmetry of the received signal and provides a measure of whether the signal's energy is concentrated before or after the mean [6]:

$$\gamma = \frac{E\left[(y(t) - \mu)^3\right]}{\sigma^3} \tag{8}$$

where, E is the expected value, $y(t)$ represents the random variable, μ is the mean, and σ is the standard deviation of $y(t)$.

Kurtosis: Kurtosis κ quantifies the deviation of values from the mean. It shows the peakedness of the signal energy distribution compared to a normal distribution, thus indicating whether a signal is more sharply peaked or more flatly distributed [6]:

$$\kappa = \frac{1}{\sigma^4 T}\int |y(t) - \mu|^4 dt \tag{9}$$

Here, σ is the standard deviation of the signal, T is the time period over which the integral is calculated, $y(t)$ is the signal, and μ is the mean of the signal.

Mean Excess Delay: The mean excess delay (MED) measures the average delay of the signal's energy relative to the arrival time of the first path. The parameter thus provides a valuable indicator of the signal's propagation conditions [6]:

$$\text{MED} = \frac{\int_{-\infty}^{\infty} t|y(t)|^2 \, dt}{\int_{-\infty}^{\infty} |y(t)|^2 \, dt} \tag{10}$$

Root Mean Squared Delay Spread: The root mean square delay spread (RDS) is a measure of the temporal dispersion of the signal's energy in the Channel Impulse Response. It represents the standard deviation of the signal delays relative to the mean. It increases when the energy is more widely spread across many delayed multipath components, a characteristic feature of NLOS scenarios [6]:

$$\text{RDS} = \sqrt{\frac{\int_{-\infty}^{\infty} (t - \tau_M)^2 |y(t)|^2 \, dt}{\int_{-\infty}^{\infty} |y(t)|^2 \, dt}} \tag{11}$$

where τ_M is the MED, as previously described in this section.

To determine robust thresholds for statistical classification, a cluster analysis was conducted based on the eight statistical features in a training phase. Instead of a simple averaging approach, the k-medoids algorithm [15] was applied to form two clusters corresponding to the LOS and NLOS classes. This approach selects actual data points as cluster centers (medoids), making it more robust to outliers than the k-Means algorithm. The Euclidean distance was used as the distance metric in the eight-dimensional feature space. After clustering, the optimal thresholds for each feature are calculated as the mean of the two cluster centers. These thresholds then serve as the basis for statistical detection, providing a clear separation between LOS and NLOS conditions. Now it is possible to classify a signal as LOS or NLOS based on the features and the previously determined thresholds. The final decision is made using a simple majority voting scheme. For each of the eight statistical features, a check is performed to determine whether its value is above or below the threshold. A counter for LOS and NLOS is then incremented based on the result. The signal is assigned to the class of the counter with the higher value. To optimize the detection performance of the statistical approach, a weighting of the features was performed. This was necessary because not all features have the same predictive power regarding LOS/NLOS conditions.

Feature	Weight	Feature	Weight
FPPL	1	ToA	2
Skewness	1	Kurtosis	1
MED	2	RDS	1
Energy Ratio	2	Total Energy	1

TABLE I: Weight of the features

Features that proved to be particularly indicative for distinguishing between LOS and NLOS were assigned a higher weight. Features whose influence was minor or which did not lead to an improvement were left with a standard weight of 1. The final, determined weighting is shown in Table I. The weights for each feature were determined through a manual optimization that used an iterative search to optimize the feature weights with the objective of maximizing the model's classification performance.

C. *Feature-Based Neural Network Approach*

This approach combines the extraction of the eight statistical features with a neural network. Unlike the manual approach, where thresholds and weights were determined experimentally, the neural network automatically learns the optimal relationships between the features. The architecture of the neural network used is based on a Deep Feedforward Neural Network (DFNN)[9] and is structured as follows:

- Input Layer: A Feature Input Layer with 8 neurons for the statistical features.
- Hidden Layers: Three fully connected layers, each with 100 neurons and a ReLU activation function.
- Output Layer: A Fully Connected Layer with 2 neurons, followed by a Softmax function to output a probability distribution for LOS and NLOS. The final decision is made by a Classification Layer.

Table II shows the training parameters of the feature-based neural network that were optimized experimentally. For the feature-based neural network, we used Adam as the optimization algorithm with a learning rate of 0.001 and 26 epochs. The minimum batch size was set to 128. We used 80% of the data for the training and 20% for validation.

Parameter	Feature-based neural network	1D-CNN
Optimization Algorithm	Adam	Adam
Learning Rate	0.001	0.003
Number of Epochs	26	12
Mini-Batch Size	128	128

TABLE II: Training parameters for the deep learning model

D. *1D-CNN Approach*

This approach differs from the feature-based methods introduced previously. It uses pre-processed received signals as input for the 1D-CNN. The 1D-CNN is well-suited for learning relevant patterns and dependencies from the signal traces without the need for explicit feature definitions. The network is designed to automatically extract features that allow a reliable distinction between LOS and NLOS signals. The architecture of the 1D-CNN is structured as follows:

- Input Layer: Sequence Input Layer with a size corresponding to the length of the received signal.
- Convolutional Layer: One-dimensional Convolutional Layer with a filter size of 3 and 16 channels, followed by a Batch Normalization Layer and a ReLU activation function.
- Feature Reduction: Global Average Pooling 1D Layer reduces the spatial dimensions of the extracted features.
- Classification Layers: Four fully connected layers with a decreasing number of neurons (32, 16, 8, 2) that process the learned features. The first three of these layers use a ReLU activation function.
- Output Layer: A Softmax Layer provides the probability distribution for the two classes, LOS and NLOS, followed by a Classification Layer that makes the final decision.

Table II summarizes the training parameters of the 1D-CNN. We optimized these parameters experimentally. The Adam optimization algorithm was used with a learning rate of 0.003 [16]. The network was trained for 12 epochs with a minimum batch size of 128. We used 80% of the data for training and 20% for validation.

V. Evaluation

A. *Measurement Setup*

We designed a measurement grid to ensure reproducible data collection. It contains 30 measurement points to capture the space well. The measurements contain a general setup with LOS and artificial NLOS-Setups, a reflection measurement, and a measurement with a focus on the first Fresnel zone.

Figure 3 illustrates the measurement grid. The grid comprised a total of 30 points spaced one meter apart.

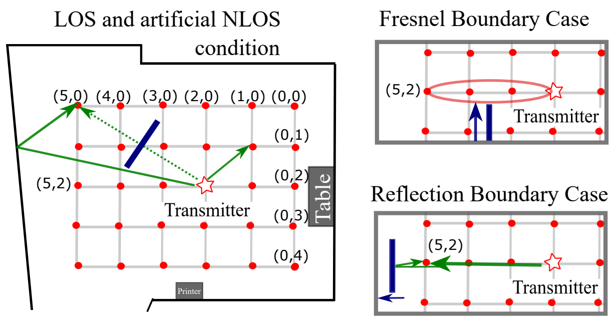


Fig. 3: Setup: Measurement grid (left), special cases reflection and Fresnel zone (right)

The transmitter was positioned at (2, 2) shown as a star. This arrangement enabled the systematic collection of UWB signals in well-defined spatial conditions. NLOS conditions were created using a whiteboard, placed at a 90-degree angle to the theoretical LOS path and halfway between the transmitter and receiver. For the boundary case analysis, we created two critical scenarios to examine the effects of reflections and the partial blockage of the first Fresnel zone. Figure 3 shows the setup on the right next to the measurement grid, for the reflection scenario. For this purpose, a whiteboard was positioned behind the receiver and moved in 15 cm steps, each corresponding to a 1 nanosecond (ns) increment in the reflection's path delay. The variable time delay ranged from 1 ns to 10 ns. The boundary case for the first Fresnel zone is shown on the right side of Figure 3. A whiteboard was placed between the transmitter and receiver and moved in 25% steps of blockage, from 0% to 100%.

B. Results

FPPL	ToA	Skewness	Kurtosis
7.7581e-06	9.2532	1.3225	4.4532
MED	RDS	E. Ratio	Total Energy
15.8001	5.6229	0.0038	1.7441e-8

TABLE III: Thresholds

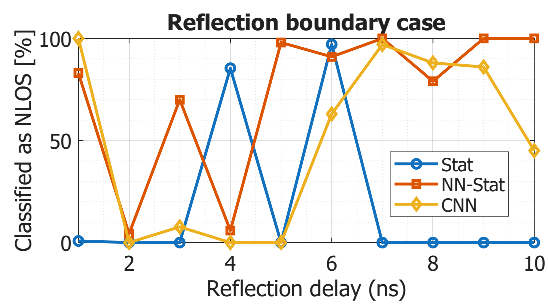
The cluster has provided the optimal thresholds listed in Table III. This table shows the optimal thresholds for the eight features used in this statistical approach. The resulting overall accuracy for the statistical approach is **60.81 %**.

Approach	Category	True	False	Accuracy	F1 Score
Statistical	LOS NLOS	500 892	613 284	44.92% 75.85%	52,71% 66,54%
Feature-based neural network	LOS NLOS	1032 1160	16 81	98.47% 93.47%	95.51% 95.99%
1D-CNN	LOS NLOS	1113 1174	2 0	99.82% 100%	99.91% 99.91%

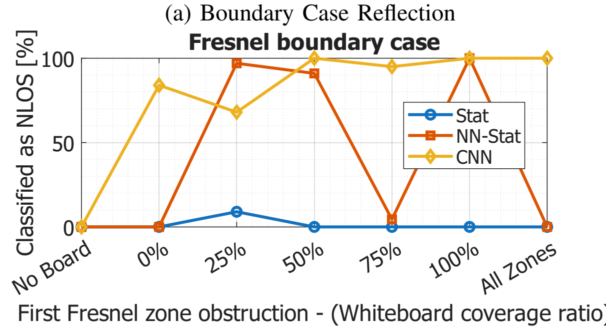
TABLE IV: Results of the approaches

As shown in Table IV, the statistical approach demonstrates a detection rate for NLOS signals of **75.85 %**. However, the accuracy for detecting LOS signals was lower at **44.92 %**. This suggests that the statistical approach tends to misclassify LOS signals as NLOS. The implementation of a neural network on the extracted features resulted in a significant improvement in detection accuracy compared to the simple statistical approach. The feature-based neural network reached **95.58 %**, a notable increase over the achieved **60.81 %** from the statistical approach previously. As shown in Table IV, the detection rate for LOS signals was **98.47 %** and the detection rate for NLOS signals was **93.47 %**. The 1D-CNN approach reached a significant improvement in classification accuracy by processing the received signals directly. This method reached **99.91 %** in classification accuracy. The detection rate for LOS signals was **99.82 %** and the rate for NLOS signals was **100.00 %** as shown in Table IV. These results confirm our hypothesis that a 1D-CNN can learn complex signal patterns that lead to a highly accurate NLOS detection.

C. Boundary Cases and independent evaluation



(a) Boundary Case Reflection



(b) Boundary Case Fresnel

Fig. 4: Comparison of boundary cases: reflection and Fresnel.

Figure 4a shows the boundary case of the reflection. The x-axis shows the delay of the first reflection in nanoseconds, and the y-axis shows the percentage of the signals classified as NLOS. In blue, the statistical approach is shown, in red, the feature-based neural network, and in yellow, the 1D-CNN. In this case, all signals were LOS, so the classification as NLOS should be very low. All approaches were unstable in delays up to 5 ns and had low accuracy from delays of 5 to 10 ns. Only the statistical approach had good accuracy from 7 to 10 ns. The 1D-CNN here shows a low performance, in particular at a delay of 1 ns and delays higher than 5 ns. In Figure 4b, results for the boundary case of the first Fresnel zone are shown. The x-axis shows the obstruction of the first Fresnel zone. Similar to Figure 4a, the y-axis shows the percentage of signals classified as LOS. As the obstruction of the first Fresnel zone increases, the classification of signals as LOS should decrease. Here, the 1D-CNN approach achieves the best results. The ideal outcome is a linear increase in the classification as NLOS, proportional to the degree of signal path blockage.

1) Independent evaluation: In addition to the train dataset, we also used a test dataset. For the test dataset, we randomly selected 10 LOS and 10 NLOS sets for random positions.

Approach	Category	True	False	Accuracy	F1-Score
Statistical	LOS	2098	1026	67.16%	57.54%
	NLOS	802	2075	27.87%	34.09%
Feature-based neural network	LOS	1980	1144	63.38%	62.59%
	NLOS	1655	1222	57.53%	58.31%
1D-CNN	LOS	1675	1449	53.62%	62.86%
	NLOS	2337	540	81.23%	70.36%

TABLE V: Results for the independent evaluation

In Table V, the results for the NLOS detection approaches are shown. The NLOS detection of the statistical approach is not reliable. The feature-based neural network approach significantly outperforms the simple statistical approach. The results of the 1D-CNN were better than the results of the feature-based neural network. While the 1D-CNN achieved a **81.23%** detection rate for NLOS signals, it incorrectly classified **1,449** LOS signals as NLOS. Our approach demonstrates high performance within the controlled measurement environment, but we acknowledge certain limitations that may affect its generalization. Firstly, the evaluation was conducted in a single, static environment. Secondly, we used artificial NLOS with a simple whiteboard. In real-world applications, the environment is not static and obstacles are varied.

VI. Conclusion and Future Work

To achieve reliable NLOS detection, three approaches were compared. Initially, a statistical approach was implemented, which extracted features from the received signal. The classification was based on thresholds found with clustering and a manual weighting of the features, which provided useful results. Next, a feature-based neural network was implemented. This model automatically learned to weight and classify the features, leading to a further increase in detection accuracy. The most innovative approach involved using a 1D-CNN, which received the channel impulse responses directly as input. This model learned relevant patterns and features from the received signal. As a result, the 1D-CNN achieved a significantly higher reliability in NLOS detection than the feature-based approaches. For future work, the first step is to expand the dataset to improve the generalization of the NLOS detection with the 1D-CNN model. Further measurement series could include outdoor scenarios, where fewer reflections tend to occur, or measurements could be conducted in rooms of different layouts and sizes. To increase the robustness of NLOS detection against environmental variability, the number, type, and position of obstacles in the measurement room could be varied.

Acknowledgments

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