Analysis of Machine Learning-Based NLOS Signal Identification Algorithm for UWB Indoor Localization Using CIR Waveform Features

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Abstract

Ultra-wideband (UWB) technology stands out among numerous indoor positioning techniques due to its high operating frequency, low interception capability, resistance to multipath effects, and strong penetration. The UWB uses the time-of-arrival (TOA) to estimate the distance between the transmitter and receiver anchors in centimeter accuracy. However, in complex indoor positioning environments, obstacles such as walls, glass windows, metal plates, and wooden doors may block and reflect signals, inevitably causing non-line-of-sight (NLOS) errors that significantly affect positioning accuracy. The NLOS signal has lower signal energy due to the reflections. Thus, the channel impulse responses (CIR) from NLOS and LOS are different. To address the NLOS signal identification issue in UWB positioning, we utilize UWB CIR data collected from various positioning scenarios as the data source. CIR waveform input features are provided for the NLOS signal recognition model, and four machine learning models—Support Vector Machine (SVM), Multi-Layer Perceptron (MLP), K-Nearest Neighbors (KNN), and XGBoost—are trained and optimized for NLOS signal recognition. The aim of the study is to analyze the performance of different machine learning algorithms for NLOS signal recognition in UWB indoor localization using these features. Experimental results indicate that machine learning-based NLOS signal recognition algorithms can achieve an accuracy of approximately 77.46%, precision of 80.46%, and an F1 score of 0.81. Among the four models, the XGBoost model demonstrates generally better recognition performance.

1. Introduction

With the continuous development of the mobile internet, society has entered a new era of massive construction in the Internet of Things (IoT). The application areas of Location-Based Services (LBS) technology are becoming increasingly extensive and crucial. For instance, in the field of autonomous vehicles, the absence of location services support would severely limit its development. In outdoor positioning applications, the Global Navigation Satellite System (GNSS) stands out among numerous outdoor positioning technologies due to its all-weather and all-time characteristics, effectively meeting the outdoor positioning requirements. In indoor positioning applications, Ultra-Wideband (UWB) technology is widely employed, holding significant development prospects. The UWB has been widely applied for the indoor navigation (Henk, 2012) due to low cost and high positioning accuracy. The commonly used UWB positioning method relies on Time Difference of Arrival (TDOA), utilizing the time difference in signal transmission and reception between the target and base stations to provide precise distance estimates. The three-dimensional coordinates of the target are then determined through the geometric relationships among multiple base stations. The schematic diagram of TDOP positioning principles is illustrated in Figure 1. However, in indoor positioning, influenced by obstacles such as walls and furniture, signal propagation between the target and base stations is not limited to Line-of-Sight (LOS) scenarios but may also include obstructed Non-Line-of-Sight (NLOS) scenarios, leading to significant distance estimation biases and, consequently, affecting the accuracy of target positioning. The schematic diagram of NLOS scenarios is presented in Figure 2.

Currently, NLOS identification methods can be broadly classified into two categories. The first category approaches the issue from the perspective of ranging accuracy, treating NLOS range measurements as outliers. These methods employ techniques such as residual weighting to smooth out anomalous signals, thereby enhancing positioning accuracy. The traditional methods treat the NLOS as an outlier, and down weights their contribution to the state estimate based on the robust estimation theory (Yang, 2002). The robust estimation methods, however, are limited by 50% of data contamination (XU, 2005). The second category focuses on wireless channel characteristics, utilizing Channel Impulse Response (CIR) data. By identifying and eliminating NLOS conditions based on CIR data, these methods aim to improve positioning accuracy (SUN, 2023).

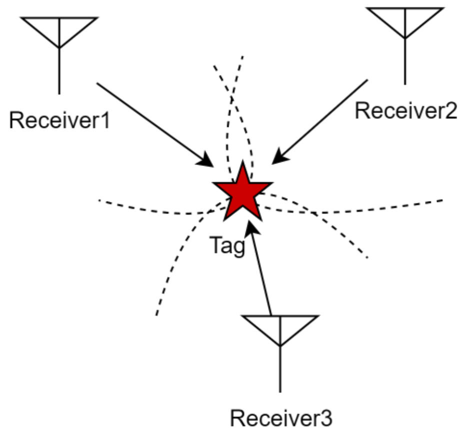

Figure 1. TDOA localization method.

With the widespread application of machine learning in wireless communication, an increasing number of scholars are utilizing machine learning methods to identify Non-Line-of-Sight (NLOS) signals. Methods such as Support Vector Machine (SVM) (Yang, 2023), Relevance Vector Machine (RVM) (Nguyen, 2015), and Multilayer Perceptron (MLP) (Klemen, 2016), as well as Random Forest (BARRAL, 2019), have been successfully applied UWB NLOS detection applications. In this paper, we use the Channel Impulse Response (CIR) waveform features to optimize the signal recognition models of SVM, MLP, and KNN, as well as XGBOOST, and assess their performance in NLOS signal recognition.

The organization of this paper is as follows: Section 2 provides a brief introduction to the machine learning algorithms employed and the input features used. In Section 3, we will present the experiments and datasets used to analyze the performance of different machine learning algorithms in NLOS signal identification. Finally, Section 4 summarizes the findings and draws conclusions.

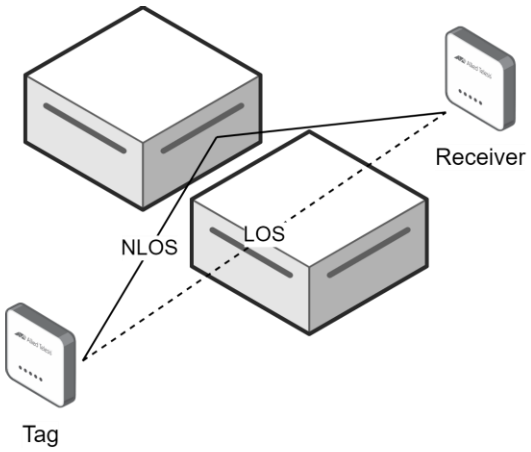

Figure 2. NLOS signal formation scenario.

2. Theory and Principles

2.1 Channel Impulse Response

The acquisition of Channel Impulse Response (CIR) is accomplished by assessing the correlation between the accumulated incoming samples and the expected pre-sequence. The calculation formula is as follows:

$$r(t) = \sum_{i=1}^{N} a_i \bullet p(t - \tau_i) + n(t) \quad (1)$$

where a_i = Amplitude
τ_i = Time Delay
$n(t)$ = Gaussian White Noise
$p(t)$ = Gaussian Radio Waveform

The UWB ranging chip offers a CIR output interface, and the analysis of the CIR waveform allows for the identification of whether the received signal is LOS or NLOS. Refer to Figures 3 and 4 for an illustration of the CIR waveforms.

In Figure 3, the CIR waveform represents a LOS signal, where the initial direct path is clearly discernible as the peak, followed by subsequent waveforms resulting from signals reflected by indoor walls. During this scenario, accurate measurement of signal reception time is achievable, with minimal impact on positioning accuracy. Figure 4 illustrates an idealized CIR waveform for a NLOS signal. In this case, multiple peaks are evident, and the first arrival peak is not the highest. Consequently, precise measurement of signal reception time is challenging, significantly affecting positioning accuracy.

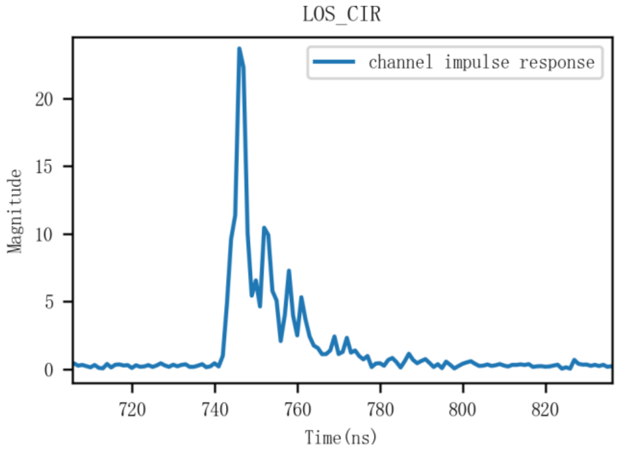

Figure 3. LOS channel impulse response.

The distinctive characteristics of CIR data under varying propagation conditions provide a theoretical foundation for utilizing machine learning methods. This foundation facilitates the extraction of CIR data features and the establishment of a mapping relationship between CIR data and ranging errors.

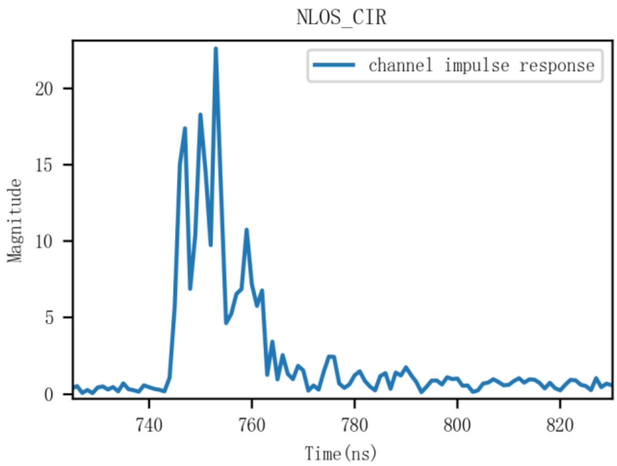

Figure 4. NLOS channel impulse response.

2.2 CIR Waveform Features

The input features for machine learning algorithm training is selected based on the differences in CIR waveforms between NLOS signals and LOS signals.

1) Energy

Energy represents the comprehensive signal processing energy, denoted as ε_r .

$$\varepsilon_r = \int_{-\infty}^{+\infty} |r(t)|^2 \, dt \quad (2)$$

2) Maximum amplitude

Maximum amplitude represents the maximum value of the amplitude during signal transmission, denoted as $r_{\max}$.

$$r_{\max} = \max_t |r(t)| \quad (3)$$

3) Rise time

Rise time represents the time it takes for the signal to go from 0.1 times the maximum amplitude to 0.9 times the maximum amplitude, denoted as t_{rise}.

$$t_{rise} = t_H - t_L \tag{4}$$

where $t_L = \min\{t : |r(t)| \ge \alpha\sigma_n\}$

$t_H = \min\{t : |r(t)| \ge \beta r_{\max}\}$, and σ_n is the standard deviation of the thermal noise. The values of $\alpha > 0$ and $0 < \beta \le 1$ are chosen empirically to capture the rise time; in our study, these values are $\alpha = 6$ and $\beta = 0.6$.

4) Mean excess delay

Mean excess delay represents an important parameter of the time dispersion characteristics of a multipath channel, denoted as T_{med}.

$$T_{med} = \int_{-\infty}^{+\infty} t\psi(t)dt \tag{5}$$

where $\psi(t) = |r(t)|^2 / \varepsilon_r$

5) Rms delay

RMS delay is another parameter, distinct from Mean excess delay, that represents the time dispersion characteristics of a multipath signal, denoted as T_{rms}.

$$T_{rms} = \int_{-\infty}^{+\infty} (t - T_{med})^2 \psi(t)dt \tag{6}$$

6) Kurtosis

Kurtosis is a statistical measure that describes the sharpness or flatness of the distribution shape of CIR waveform data.

$$\kappa = \frac{1}{\sigma_{|r|}^4 T} \int_T \left[|r(t) - \mu_{|r|}| \right]^4 dt \tag{7}$$

where $\mu_{|r|} = \frac{1}{T} \int_T |r(t)| dt$

$$\sigma_{|r|}^2 = \frac{1}{T} \int_T \left[|r(t)| - \mu_{|r|} \right]^2 dt$$

2.3 Machine Learning Algorithm

1) SVM

SVM is a commonly used classification model, with its fundamental principle centered around maximizing the margin to construct the classifier. SVM exhibits strong capabilities in handling high-dimensional data and possesses excellent characteristics in classification performance and generalization. Therefore, SVM finds extensive application in the field of NLOS signal recognition. In SVM algorithms, the selection of kernel functions and regularization parameters (C) significantly impacts the model's recognition effectiveness. In this study, we adopted the radial basis kernel function. Regarding the selection of C values, we tested SVM models with C values ranging from 0 to 100 on a subset of the dataset to assess their recognition effectiveness. The selection of a subset of the dataset was to ensure the efficiency of optimizing the model. As depicted in Figure 5, the model's recognition effectiveness is optimized when the C values is set to 77.

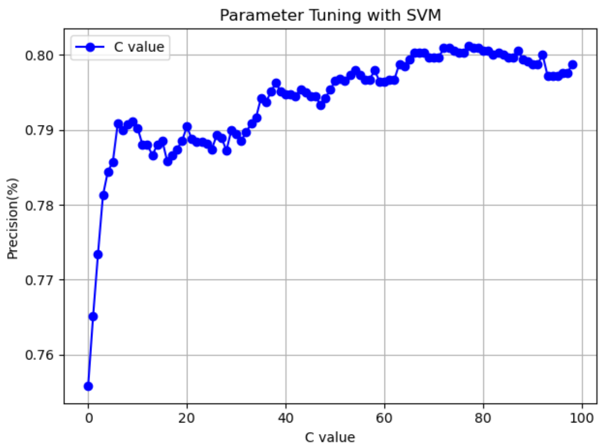

Figure 5. Parameter tuning with SVM.

2) MLP

MLP, a machine learning algorithm based on the structure of a feedforward neural network, encompasses an input layer, hidden layers, and an output layer, with each layer fully connected to the next. The schematic diagram of the MLP model framework is shown in Figure 6. The number of neurons in the input layer is determined by the input features, while the number of neurons in the output layer is determined by the number of target classes. The number of hidden layers and the number of neurons per layer are determined based on the specific application, significantly impacting the classifier's classification performance. In our experimentation, we explored four different configurations of hidden layers and tested their recognition effectiveness on a subset of the dataset used in this study. As depicted in Table 1, the model's recognition effectiveness is optimized when there are three hidden layers, each containing 100 neurons.

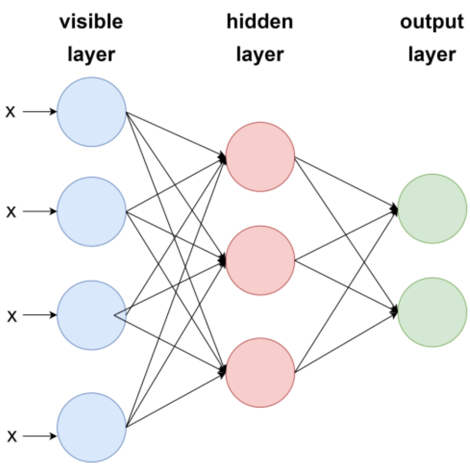

Figure 6. Schematic diagram of the MLP model framework.

Hidden Layer	Precision
(50)	74.71%
(100,)	77.20%
(50,50,50)	76.04%
(100,100,100)	77.69%

Table 1. Different choice of hidden layer configuration affects precision.

3) KNN

K-Nearest Neighbors (KNN) is a fundamental supervised learning algorithm utilized for classification and regression tasks. Its basic principle involves predicting the label of an unlabeled sample by searching for the nearest labeled samples in the feature space. In the KNN model, the settings of n_neighbors and weights significantly impact the model's recognition effectiveness. We conducted experiments testing the recognition effectiveness of the model under different settings of n_neighbors ranging from 1 to 100, using both "uniform" and "distance" weights settings. As illustrated in Figure 7, the model performs optimally when n_neighbors is set to 5 and weights are set to "uniform".

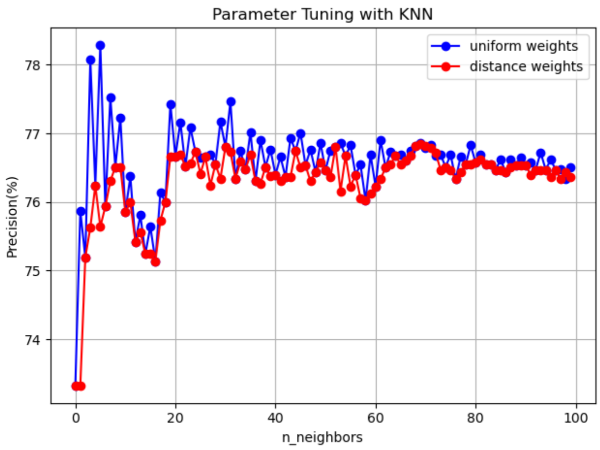

Figure 7. Parameter tuning with KNN.

4) XGBOOST

XGBOOST, an ensemble gradient boosting model proposed on the foundation of the Gradient Boosting Decision Tree (GBDT) algorithm, adopts an integrated approach to iteratively train weak learners, thus improving the model's performance. The framework diagram of the XGBOOST model is shown in Figure 8. In the field of NLOS signal recognition, numerous identification algorithms are based on decision tree models. XGBOOST, functioning as an algorithm that integrates multiple decision trees, continuously generates new trees to fit the residuals of preceding tree models, thereby reducing loss and achieving superior results. In this paper, the settings for the XGBOOST model are presented in Table 2.

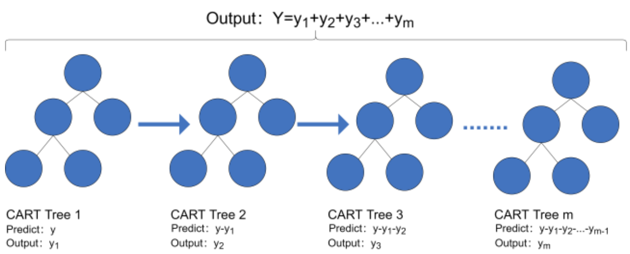

Figure 8. Schematic diagram of the XGBOOST model framework.

Setting	Value
learining_rate	0.1
max_depth	12
n-estimators	500

Table 2. Settings for the XGBOOST.

Based on the results of hyperparameter tuning for the four models, the final hyperparameter configurations for the four machine learning models can be found in Table 3.

Setting	Model
	SVM
Kernel C	“rbf” 77
	MLP
Hidden Layer	(100,100,100)
	KNN
n_neighbors weights	5 uniform
	XGBOOST
learining_rate max_depth n-estimators	0.1 12 500

Table 3. Parameter settings for the four models.

3. Experiment

3.1 Dataset

This study utilized the open-source UWB dataset provided by Klemen. The dataset employs the low-cost DecaWave DW1000 UWB sensor and was collected in seven different indoor environments, including Office, small apartment, small workshop, kitchen with a living room, bedroom, and boiler room. In each indoor location, 3000 LOS samples and 3000 NLOS samples were collected. The selection of diverse locations aims to prevent the creation of location-specific LOS and NLOS models. In total, 42,000 samples were collected, with 21,000 for LOS and 21,000 for NLOS channel conditions. To prepare the dataset for constructing LOS and NLOS models, the samples were randomized to avoid overfitting the model to specific locations. Two UWB nodes were used for measurements: one as an anchor and the second as a tag. The dataset exclusively includes traces of LOS and NLOS channel measurements without any reference positioning, making it unsuitable for localization evaluation.

3.2 Experiment Result

The confusion matrix is commonly used for the visualization of supervised learning outcomes. For binary classification, the resulting classification can be divided into four categories: True Positive (TP), False Negative (FN), False Positive (FP), and True Negative (TN). The schematic diagram of the confusion matrix is shown in Figure 9. To evaluate the performance of the model, standard metrics based on the confusion matrix are provided, including accuracy, precision, recall, and F1 score, defined mathematically as follows:

$$accuracy = \frac{(TP+TN)}{(TP+TN+FP+FN)} \tag{8}$$

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$$precision = \frac{TP}{TP + FP} \tag{9}$$

$$recall = \frac{TP}{TP + FN} \tag{10}$$

$$F = 2 \times \frac{precision \times recall}{precision + recall} \tag{11}$$

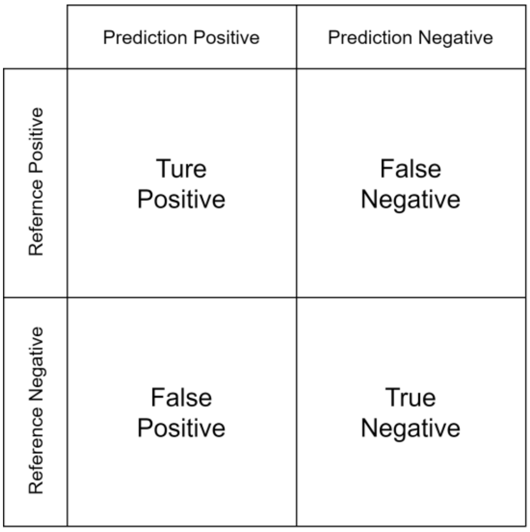

Figure 9. confusion matrix.

Using the dataset introduced in Section 3.1, we trained four machine learning models: SVM, MLP, KNN, and XGBOOST. We analyzed the models' performance under the same inputs. The dataset was randomly divided into training and testing sets in a ratio of 80% to 20%. The classification results' confusion matrices for the four models and standard performance metrics based on the confusion matrix are shown in Figure 10 and Table 3, respectively.

From the experimental results, the precision of NLOS signal recognition for the four models are 78.2%, 77.85%, 77.85%, and 75.96%, with an average precision of 77.46%. Among them, XGBOOST exhibited the best recognition performance. The accuracy of the models is 82.8%, 81.76%, 80.29%, and 76.99%, with an average accuracy of 80.46%. Specifically, XGBOOST achieved the highest overall precision. The F1 scores for the four models are 0.84, 0.83, 0.81, and 0.77, with an average F1 score of 0.81.

It can be observed that the models exhibit relatively poor performance in NLOS signal recognition. An analysis of this phenomenon reveals that the dataset used was collected from various indoor environments, where different materials obstructing signal propagation may have varied impacts on the training feature information. Overall, XGBOOST performed the best among the four machine learning models used in this study, while the KNN model showed poorer performance.

Model	Score			
	accuracy	precision	recall	F1
XGBOOST	82.80%	78.20%	90.27%	0.84
SVM	81.76%	77.85%	88.04%	0.83
MLP	80.29%	77.85%	83.67%	0.81
KNN	76.99%	75.96%	78.00%	0.77

Table 4. Standard metrics results for the four models.

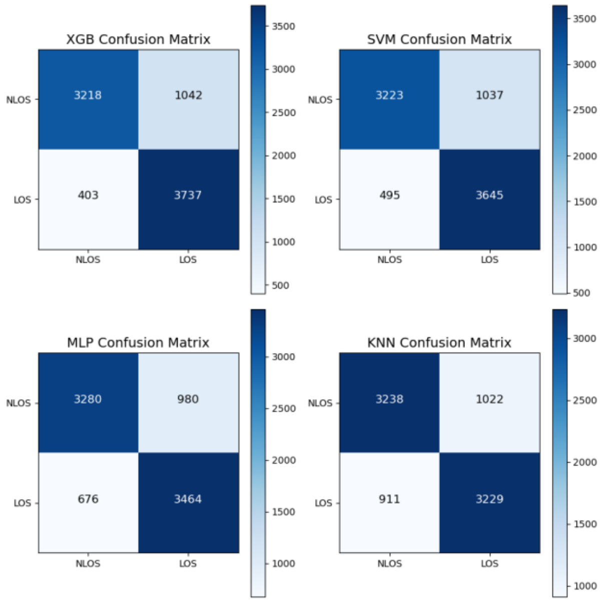

Figure 10. confusion matrix results for the four models.

4. Conclusion

This paper introduces the CIR waveform features of used NLOS signal recognition models, trains four machine learning classifiers: SVM, MLP, KNN, and XGBOOST, and evaluates their performance in NLOS signal recognition. The results indicate that machine learning-based NLOS signal recognition algorithms achieve an precision of approximately 77.46%, a accuracy of 80.46%, and an F1 score of 0.81. Among the four models, the XGBOOST model demonstrates relatively superior overall recognition performance. This study provides a theoretical basis and practical reference for low-cost UWB indoor positioning methods.

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