# Fuzzy Comprehensive Evaluation based NLOS Identification for UWB Indoor Positioning

Jinkun Li [1], Chundi Xiu [1], Feng Wang [1], Maria S. Selezneva [3], Dongkai Yang [1,2]

1. Department of Electronic and Information Engineering, Beihang University, Beijing 100191, China - jkl_Reuben@163.com, xcd@buaa.edu.cn, wangfeng11584@buaa.edu.cn, 07081@buaa.edu.cn
2. International Innovation Institute, Beihang University, Hangzhou 311115, china
3. Department of Automatic Control Systems, Bauman Moscow State Technical University, Russia - m.s.selezneva@mail.ru

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## Abstract

Ultra-wideband (UWB) positioning technology stands out from many indoor positioning technologies with its advantages of high precision. However, non-line-of-sight (NLOS) propagate leads to heavy range error and reduces position accuracy, this paper proposes a NLOS identification method based on channel impulse response (CIR), which includes three stages. Firstly, CIR based feature selection is carried out, which includes correlation analysis of calculated features. Secondly, fuzzy comprehensive evaluation model is introduced to NLOS identification. Finally, time of arrival (TOA) based location estimation is realized after NLOS ranging error mitigation. Simulation results show that the average identification rate of NLOS can exceed 86%, and the average positioning error can be reduced by about 0.5m.

## 1. Introduction

With the rapid development of society, location-based service (LBS) has become a critical research hotspot. The Global Navigation Satellite System (GNSS) can accurately determine outdoor positions, meeting basic needs. However, obstacles such as buildings make it difficult for satellite signals to penetrate indoors, rendering indoor positioning impossible. People spend most of their time in indoor activities, so many technical methods (Zeakvat et al., 2021) for indoor positioning (Yassin et al., 2017) have emerged. Among them, UWB (Oppermann and Iinatti, 2004) positioning stands out because of its advantages of high positioning accuracy (Ruming, 2009). It is a range-based positioning method that relies on accurate signal transmission time of both positioning parties, but its signal is affected by obstacles and generates multi-path interference, resulting in reduced ranging accuracy. Furthermore, the positioning accuracy error in some signal blocking areas is significant, which does not meet people’s needs.

Many scholars have studied the NLOS problem of UWB signals, which is usually solved from two aspects: identification and mitigation. NLOS identification can be divided into three categories from different levels of data processing, including channel feature based methods, distance based methods and location based methods. Among them, the location based method is to identify after position calculation (Schroeder et al., 2007), and this method is only effective when assisted by redundant distance information, that is, to identify the exclusion by comparing the position coordinates calculated by different distance information. The distance based identification method is carried out before and after the location calculation (Borras et al., 1998) by means of data processing methods such as probability density function and variance, and to some extent depends on the limitations of prior conditions such as prior distribution function. Identification methods based on channel characteristics usually extract channel impulse response and detect different characteristics obtained based on it, including total signal energy, maximum signal amplitude, signal-to-noise ratio, average delay, etc (Yu et al., 2019). Feature analysis methods are divided into two categories. One is to analyze the statistical characteristics of different characteristics and set thresholds for comparison, so as to identify whether it is NLOS. The other is to use machine learning such as support vector machine, neural network to perform classification tasks. Gururaj etc. (Gururaj et al., 2017) discusses NLOS detection based on kurtosis, mean excess delay spread, root mean square delay spread, receiving power and first path power. Zeng etc. (Zeng et al., 2019) uses features extracted from the CIR (such as kurtosis, standard deviation, energy, etc.) for classification with the help of machine learning algorithms. Unlike existing methods, the NLOS and LOS probability density functions for the correlation coefficients are calculated using the training data. Si etc. (Si et al., 2023) proposes a novel LOS/NLOS identification algorithm based on multi-layer perceptrans (MLP), which can utilize both manually extracted features and CNN features based on raw CIR inputs, adopting a machine learning approach that has congenital limitations due to its large amount of prior information required. In addition, some scholars use additional environmental information, including the spatial structure of buildings and maps (Jo et al., 2006), to identify NLOS (Gustafson et al., 2006), which is similar to the map matching method in indoor positioning. However, such constraints cannot guarantee access at any time, so this method has certain shortcomings. There are usually two kinds of methods for mitigating ranging error in NLOS environment. One is to correct the range error after the identification of NLOS, and then use the corrected distance to solve the position. Heidari et al. Heidari (Heidari et al., 2007) subtracted the range error from the NLOS range estimate based on the range error statistics associated with the position of each class of receivers. The other is to directly discard the ranging error value in NLOS environment, and use additional localization sources, such as inertial measurement unit (IMU) and geomagnetic, to study the multi-source fusion localization algorithm. In one reference (Xia et al., 2018), the authors propose a Pedestrian dead reckoning (PDR) assisted ultra-wideband positioning method to realize switching between two positioning systems. The position difference between UWB and PDR is applied to a formula based on probability distribution. Weighted aver-


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age is chosen as the fusion method. The positioning error of UWB is reduced by PDR (Tong et al., 2020). As a more advanced approach, the authors of (Liu et al., 2019) propose a new method using the position difference of an extended Kalman filter (EKF). Kim (Kim and Pyun, 2021) proposes a hybrid positioning system that fully combines UWB and PDR, which divides the NLOS of UWB into LOS, weak NLOS and hard NLOS, uses a fusion method based on Kalman filtering (KF) to identify the NLOS environment, and alleviates the UWB error through PDR. In addition, there are also attempts to combine the two mitigation methods, but the complexity of the system is increased to a certain extent.

Based on the above existing research on NLOS identification and mitigation in UWB positioning, this paper proposes a CIR based NLOS identification method. Through correlation analysis of different channel characteristics, features with large differences are selected for identification, and then fuzzy comprehensive evaluation (FCE) model is adopted for quantification. Determine NLOS situation by comparing it with the experience threshold. In the ranging error mitigation of NLOS, the range correction is determined by ranging error statistical characteristic. The advantage of this method is that it does not require too much prior information and the complexity of the algorithm is much lower than other methods such as machine learning. In addition, the NLOS identification and the positioning errors before and after mitigation are compared and the proposed algorithm is validated.

The remainder of the paper is organized as follows. In section 2, it introduces the concrete methods of NLOS identification and ranging error mitigation; the third section describe the used dataset and some simulation experiments are conducted in this section to verify the performance of the proposed algorithm. And conclusions are given at last.

## 2. Method of NLOS Identification

The overall block diagram of the system is shown in Figure 1, and the system is divided into three stages as a whole, including feature selection based on CIR, NLOS identification based on FCE, and localization estimation based on TOA. In the first stage, it mainly consists of feature calculation and correlation analysis of the raw data based on CIR to screen out the features for NLOS identification; in the second stage, the FCE model is used for NLOS identification; finally, the ranging values in the NLOS environment are calibrated by analysing the statistical characteristics of the ranging error values and the location estimation is performed using the calibrated ranging values.

### 2.1 CIR Based Feature Selection

**2.1.1 Feature Calculation** Based on CIR, a variety of typical features are extracted from the signal waveform for the identification of NLOS. When the signal is blocked by obstacles, there will be a multi-path effect, the energy will be greatly attenuated, the noise will also be accompanied by a great change, and the pulse rise time will change significantly. In the case of LOS without multi-path interference, kurtosis (KUR) is higher, but in the presence of multi-path interference, KUR will decrease significantly. Based on this, the following six potential influence characteristics are selected in this paper, which are total energy (TE), maximum amplitude (MA), signal-to-noise ratio (SNR), rise time (RT), mean excess delay (MED) and KUR. These features are calculated as follows:

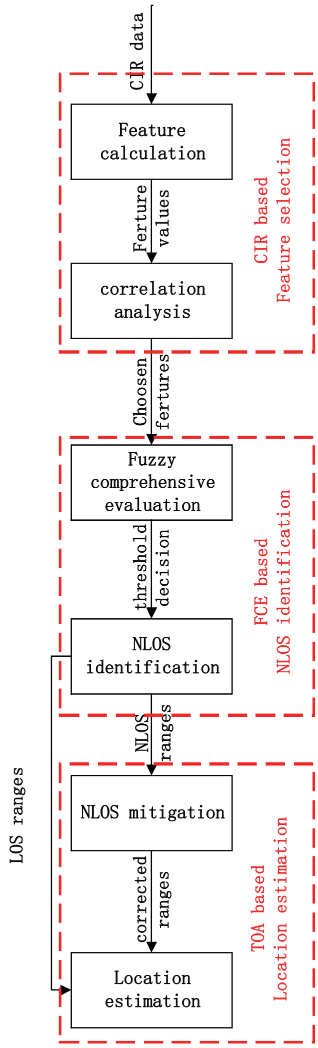


Figure 1. Overall block diagram.

1) TE.

$$\varepsilon = \sum_{i=1}^{N} |r(t_i)|^2, \tag{1}$$

where $r(t_i)$ = the amplitude of $i$th UWB signal waveform sample
$N$ = the number of samples

2) MA.

$$r_{\max} = \max\{|r(t_i)|\}, \tag{2}$$

3) SNR.

$$\delta_{snr} = 10\log_{10}\left(\frac{r_{\max}^2}{2\sigma_n^2}\right), \tag{3}$$

where $\sigma_n$ = the standard deviation of the thermal noise

4) RT.

$$t_{rise} = t_{stop} - t_{start}, \tag{4}$$

with

$$\begin{cases} t_{start} = \min\{t_i : |r(t_i)| \geq 0.1 r_{\max}\} \\ t_{rise} = \min\{t_i : |r(t_i)| \geq 0.9 r_{\max}\} \end{cases}$$

where $t_i$ = the time of $i$th UWB signal waveform sample

5) MED.

$$\tau_{med} = \frac{1}{\varepsilon}\sum_{i=1}^{N}(t_i|r(t_i)|^2), \tag{5}$$

6) KUR.

$$\kappa = \frac{1}{N\sigma_r^4}\sum_{i=1}^{N}(|r(t_i)-\mu_r|)^4, \tag{6}$$

with

$$\mu_r = \frac{1}{N}\sum_{i=1}^{N}(|r(t_i)|), \sigma_r^2 = \frac{1}{N}\sum_{i=1}^{N}(|r(t_i)-\mu_r|)^2.$$

Before the correlation analysis of the signal characteristics, it is necessary to eliminate the abnormal values in each characteristic value, and some extreme values will affect the correlation judgment between the two characteristics.

**2.1.2 Correlation Analysis** The correlation coefficient reflects the direction and degree of the change trend between the two variables, and its absolute value ranges from 0 to 1, 0 indicates that the two variables are not correlated, larger values indicate stronger correlation. Correlation coefficients usually include Pearson, Spearman and Kendall correlation coefficients. Pearson correlation coefficient has high requirements on data, that is, the overall normal distribution of two variables, and the observed values are continuous and independent of each other. The signal characteristic data such as TE and MA in this paper do not meet the conditions. In contrast, Spearman and Kendall correlation coefficients have no additional data condition requirements, so this paper chooses these two correlation coefficients for comparative analysis.

Spearman's correlation coefficient is calculated by equation (7).

$$\rho = 1 - \frac{6\sum d_i^2}{n(n^2-1)}, \tag{7}$$

Take two pairs of data TE and MA as an example, $d_i$ represents the difference of the position value of the $i$th data pair; $n$ represents the total number of observed samples.

Kendall coefficient is based on the idea of collaboration. For the two pairs of observations, if the observations are positively correlated, it says that the two pairs of observations are harmonious, otherwise they are disharmonious. The calculation is shown in equation (8).

$$\rho = \frac{2(m-k)}{n(n-1)}, \tag{8}$$

Taking TE and MA as two pairs of data, $m$ represents the logarithm of harmonious observations between the two sets of data, $k$ represents the logarithm of disharmonious observations between the two sets of data, and $n$ represents the total number of observed samples.

Finally, the correlation coefficients between the six characteristics are obtained, and the correlation is strong. Only one of the two eigenvalues is used for NLOS identification.

## 2.2 FCE Based NLOS Identification

In the identification of NLOS, the idea of FCE is adopted. This comprehensive evaluation method transforms qualitative evaluation into quantitative evaluation according to the membership theory of fuzzy mathematics, and gives a general judgment on the NLOS identification problems related to various signal characteristics based on CIR. The steps are as follows:

1) Factor set: The factor set is the signal feature screened by correlation analysis;

2) Comments set: The review sets are LOS and NLOS;

3) The weight of each factor, that is, the role of each factor in the comprehensive evaluation. In the case of data, this paper adopts the entropy weight method to determine the weight of each factor. For the normalization of index values, this paper adopts the maximum-minimum normalization method, and as shown in equation (9).

$$Y_{ij} = \frac{X_{ij} - \min(x_i)}{\max(x_i) - \min(x_i)}, \tag{9}$$

where $X_{ij}$ = the original value of different features
$Y_{ij}$ = the normalized value of different features

Calculate the weight $p_{ij}$ of the index value of the $i$th item of the $j$th index, and as shown in equation (10).

$$p_{ij} = Y_{ij} / \sum_{i=1}^{n} Y_{ij}, \tag{10}$$

Calculate the entropy of the $j$th index, and the formula is in equation (11).

$$E_j = -\ln(n)^{-1}\sum_{i=1}^{n} p_{ij}\ln p_{ij}, \tag{11}$$

Calculate the entropy of each index, and the formula is in equation (12).

$$W_i = \frac{1-E_i}{k-\sum E_i}, \tag{12}$$

Then it gets the weight set $A$.

4)The fuzzy comprehensive judgment matrix is determined, and membership function is selected to calculate membership degree. The membership function is shown in equation (13).

$$r_{ij} = 1 - \left|\frac{x_{ij} - ((\max(x_j) - \min(x_j))/2)}{\max(x_{ij}, (\max(x_j) - \min(x_j))/2)}\right|, \tag{13}$$

where $x_j$ = the index value of the all item of the $j$th evaluation index
$Y_{ij}$ = the normalized value

The evaluation matrix $R$ which is consisted in $r_{ij}$ is obtained.

5)The model formula of FCE is shown in equation (14).

$$B = A * R, \tag{14}$$


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Finally, the computed affiliation $B$ is compared with the empirical threshold to determine whether it is in NLOS situation. Thresholds are selected from empirical values of a priori information processing of established environments, between 0.2 and 0.5.

### 2.3 TOA based localization estimation

In this paper, the ranging error mitigation process will make a statistical analysis of the obtained range error value, mainly including its mean and variance. The specific error correction formula is in equation (15).

$$d = \frac{d_{mean}}{1 - d_{\text{var}}}, \tag{15}$$

Where $d_{mean}$ is the mean ranging error and $d_{\text{var}}$ is the ranging error variance. The participation of the mean is to effectively reduce the range error, while the participation of the variance is to adjust the error substantially in case of extreme outliers of the error.

The overall description of the method proposed in this paper is shown in Table 1.

**Algorithm 1** NLOS identification, mitigation and location estimation
**Input:** raw data of UWB signal measurements
**Output:** identification rate, range and position estimation corrected value

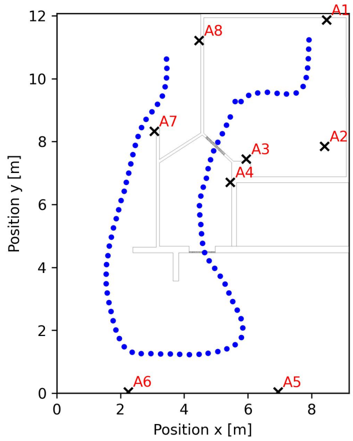
**for** ii = 1:the number of groundtruth Coordinate in one environment
  **[NLOS identification and mitigation:]**
  **for** h = 1:the number of base stations
    feature calculation absed on raw data of UWB signal measurements, correlation analysis and choose better feature set;
  **end**
    The entropy weight method calculates the weights and is used for fuzzy comprehensive evaluation, which gets membership value;
  **if** membership value $<$ threshold value
    determine as LOS and correct range;
  **else**
    determine as NLOS;
  **end**
  **[Location estimation:]**
  **if** the number of LOS base station $\geq 3$
    TOA is used for location estimation;
  **else**
    LOS base stations are selected and NLOS base stations were randomly selected for location estimation;
  **end**
**end**

Table 1. The proposed algorithmic process.

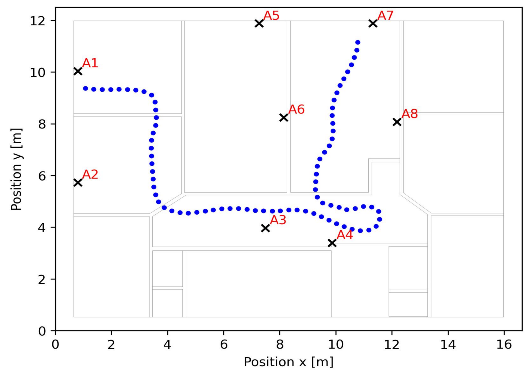
## 3. Simulation and Result

### 3.1 Dataset Description

The simulation validation data for this paper comes from Professor Klemen Bregar of the Jozef Stefan Institute, SensorLab, Slovenia (Bregar, 2023). The dataset consists of measurements from different indoor environments, each with eight fixed anchor devices and one mobile positioning device. The device was selected as a low-cost, commercially available DecaWave DW1000 (now named Qorvo DW1000) UWB transceiver in the form of a certified and integrated RF module DWM1000 with a sampling frequency of 64MHz. The environments are shown in Figure 2.




(a) scenario 1




(b) scenario 2

Figure 2. Experiment scenarios (figure from open dataset description)

In each environment, a person walking path is defined in advance, and the location of the positioning device is obtained by evenly sampling the path. At each location, multiple ranging and CIR data between the positioning device and each anchor point were collected. A total of about 0.6 million sets of measurement data were collected in two environments. Each piece of data contained 27 parameter information such as label position, anchor point position, RSS, maximum noise, etc., part of them are as shown in Table 2.

### 3.2 Feature Selection Analysis

The correlation among the six candidate features is shown in Figure 3. The two feature values with an absolute value less than 0.4 are weakly correlated. The two eigenvalues of 0.4-0.6 are moderately correlated. Two eigenvalues greater than 0.6 are considered to be strongly correlated. It can be seen that there are significant correlations between RT and MED, RT and MED, and MED and KUR. Other features showed weak correlation at different levels. Therefore, this paper intends to select four features, such as TE, MA, SNR and RT as selected features, and compare and analyze them with full features and other feature subsets.

| Member | Description |
|---|---|
| x tag | Tag position on x-axis |
| y tag | Tag position on y-axis |
| z tag | Tag position on z-axis |
| x anchor | Anchor position on x-position |
| y anchor | Anchor position on y-position |
| z anchor | Anchor position on z-position |
| NLOS | NLOS situation |
| range | Measured range |
| rss | Measured max RSS value for UWB packet |
| rss fp | Measured first RSS value for UWB packet |
| max noise | Max value for noise from UWB packet reception |
| stdev noise | Std for noise from UWB packet reception |
| cir | List of CIR values in a complex form |
| cir power | Max absolute value of CIR |
| fp point1 | Absolute value of first CIR point |

Table 2. Raw data parameter information.

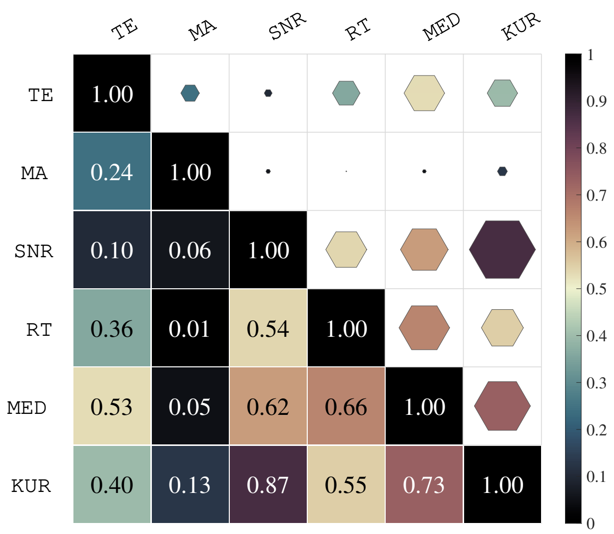
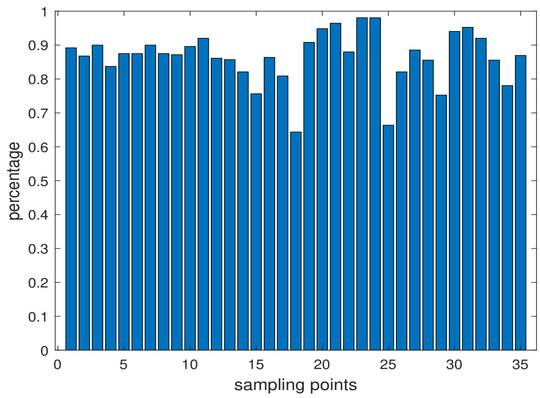


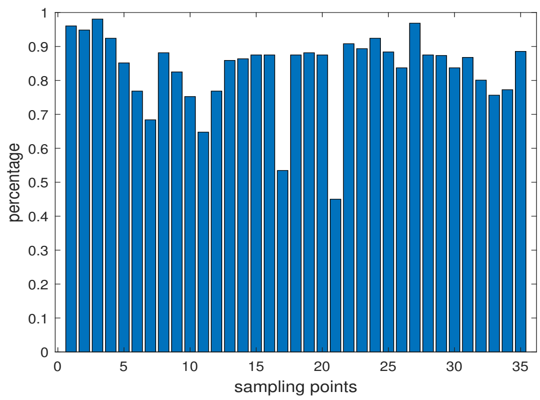

Figure 3. Figure of correlation coefficient matrix.

| Feature set | Identification rate | |
|---|---|---|
| | Ex.1 | Ex.2 |
| TE,MA,SNR,RT,MED,KUR | 89.6% | 87.1% |
| TE,MA,SNR,RT | 88.9% | 86.3% |
| TE,MA,RT | 87.5% | 85.5% |
| TE,MA | 87.4% | 83.3% |

Table 3. Identification rate in different scenarios.




(a) scenario 1




(b) scenario 2

Figure 4. Identification rate of different trajectory points in different scenarios

### 3.3 Performance of NLOS Identification

Table 3 is a comparison table of identification rates under different candidate feature combinations in four scenarios. It can be seen that the identification rate of NLOS is close to that of other combination of feature values when considering four features and six features and Computational resource consumption based on four features is slightly lower than six features.

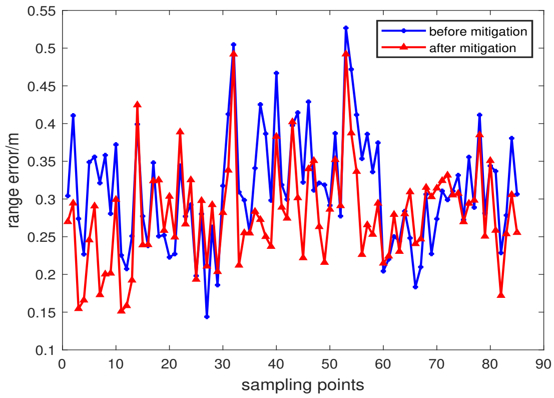
Figure 4 shows the range statistics of the NLOS identification rate in the four scenarios under the five candidate features, and it can be seen that the NLOS identification rate is lower than 80% at all the trajectory points only at individual trajectory points, and more than half of the trajectory points have a identification rate of greater than 85%, with the highest identification rate exceeding 95%.

### 3.4 the Result of Location Estimation

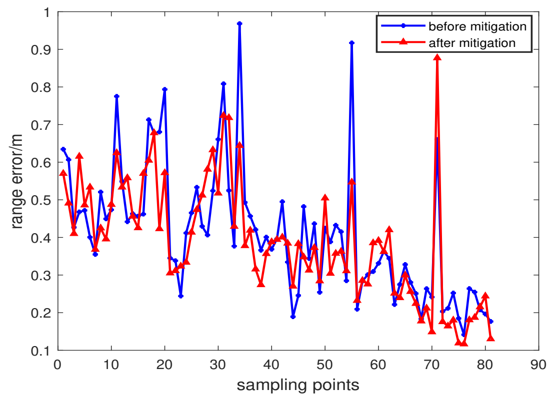
The statistics of mean ranging errors in different scenarios are shown in Table 4. The statistical diagram of ranging errors of all track points in the two scenarios is shown in Figure 5.

| environment | mean range error/m | |
|---|---|---|
| | before mitigation | after mitigation |
| Ex.1 | 0.306 | 0.259 |
| Ex.2 | 0.177 | 0.146 |

Table 4. Mean ranging error in different scenarios.

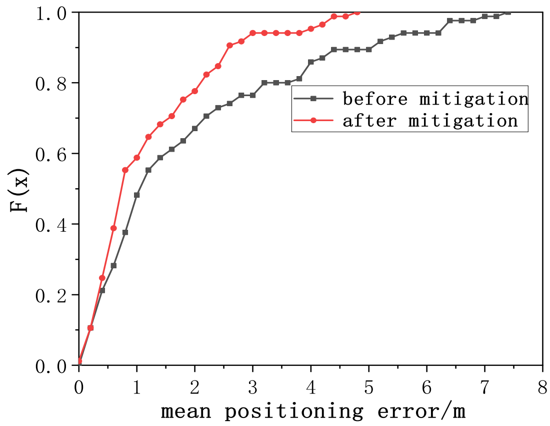



(a) scenario 1

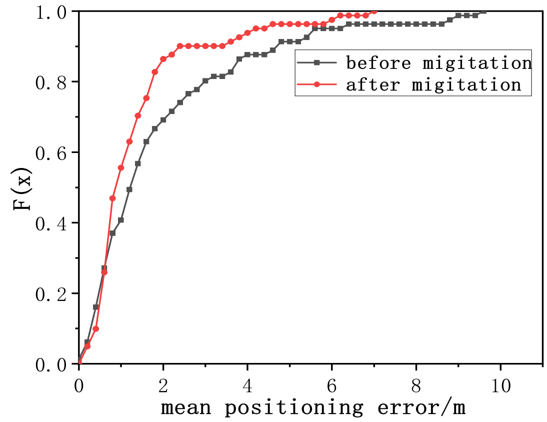



(b) scenario 2

Figure 5. Different trajectory of range error in different scenarios




(a) scenario 1




(b) scenario 2

Figure 6. The curve of CDF in different scenarios

As can be seen from Table 4 and Figure 5, compared with before NLOS ranging error mitigation, the error after mitigation is reduced by more than 0.1m on average, effectively correcting the ranging value, and the positive effect will be multiplied and reflected in the accuracy of subsequent position estimation. For some extreme ranging outliers, it can be seen that this part of the error is also effectively mitigated.

From the perspective of positioning performance estimation, the mean value, standard deviation and cumulative distribution function of positioning errors are used as evaluation indexes. The positioning accuracy performance pairs of different positioning methods are shown in Table 5, and the CDF curve is shown in Figure 6.

| environment | positioning error/m | | |
|---|---|---|---|
| | mean | STD | RMS |
| Ex.1 before | 2.435 | 3.046 | 3.446 |
| Ex.1 after | 1.873 | 2.302 | 2.943 |
| Ex.2 before | 2.116 | 2.442 | 2.932 |
| Ex.2 after | 1.775 | 1.883 | 2.157 |

Table 5. Location estimation error in different scenarios.

As can be seen from the walking trajectory map in Figure 2, the experiments in the two environments were greatly affected by NLOS due to the influence of building walls etc., while the average positioning error of all the trajectory points before and after NLOS identification and ranging error mitigation by this paper has been reduced by 0.5m, which effectively improves the problem of error attenuation caused by NLOS.

## 4. Conclusion

UWB is one of the slam dunks among many technical means for indoor positioning, which has the absolute advantage of high positioning accuracy, but is slow to be promoted in the field because it is affected by NLOS. In this paper, based on the existing research, a NLOS processing method based on channel impulse response is proposed, including CIR based feature selection, FCE based NLOS identification and TOA based localization estimation. Simulation experiments and analysis show that this method can effectively identify NLOS, the average identification rate can exceed 86%. Besides, the range error can be effectively corrected, which contributes to the position estimation error reduced by about 0.5m. The methodology proposed in this paper provides new insights for subsequent research on

NLOS identification, and promotes the study of more effective methods in NLOS ranging error mitigation.

## References

Borras, J., Hatrack, P., Mandayam, N., 1998. Decision theoretic framework for nlos identification. *VTC '98. 48th IEEE Vehicular Technology Conference. Pathway to Global Wireless Revolution (Cat. No.98CH36151)*, 2, 1583–1587 vol.2.

Bregar, K., 2023. Indoor UWB Positioning and Position Tracking Data Set. *SCIENTIFIC DATA*, 10(1).

Gururaj, K., Rajendra, A. K., Song, Y., Law, C. L., Cai, G., 2017. Real-time identification of nlos range measurements for enhanced uwb localization. *2017 International Conference on Indoor Positioning and Indoor Navigation (IPIN)*, 1–7.

Gustafson, D., Elwell, J., Soltz, J., 2006. Innovative indoor geolocation using rf multipath diversity. *2006 IEEE/ION Position, Location, And Navigation Symposium*, 904–912.

Heidari, M., Akgul, F. O., Pahlavan, K., 2007. Identification of the absence of direct path in indoor localization systems. *2007 IEEE 18th International Symposium on Personal, Indoor and Mobile Radio Communications*, 1–6.

Jo, Y.-H., Lee, J.-Y., Ha, D.-H., Kang, S.-H., 2006. Accuracy enhancement for uwb indoor positioning using ray tracing. *2006 IEEE/ION Position, Location, And Navigation Symposium*, 565–568.

Kim, D.-H., Pyun, J.-Y., 2021. NLOS Identification Based UWB and PDR Hybrid Positioning System. *IEEE Access*, 9, 102917-102929.

Liu, F., Wang, J., Zhang, J., Han, H., 2019. An Indoor Localization Method for Pedestrians Base on Combined UWB/PDR/Floor Map. *SENSORS*, 19(11).

Oppermann, I, M. H., Iinatti, J., 2004. UWB Theory and Applications (Oppermann/UWB: Theory and Applications) —— Front Matter. i-xxiv.

Ruming, C., 2009. UWB technology development prospect and its frequency plan. *Mobile Communications*, 33, 71-74.

Schroeder, J., Galler, S., Kyamakya, K., Jobmann, K., 2007. Nlos detection algorithms for ultra-wideband localization. T. Kaiser, K. Jobmann, K. Kyamakya (eds), *WPNC'07: 4TH WORKSHOP ON POSITIONING NAVIGATION AND COMMUNICATION 2007, WORKSHOP PROCEEDINGS*, Workshop on Positioning Navigation and Communication, 159+.

Si, M., Wang, Y., Siljak, H., Seow, C., Yang, H., 2023. A Lightweight CIR-Based CNN With MLP for NLOS/LOS Identification in a UWB Positioning System. *IEEE Communications Letters*, 27(5), 1332-1336.

Tong, H., Xin, N., Su, X., Chen, T., Wu, J., 2020. A Robust PDR/UWB Integrated Indoor Localization Approach for Pedestrians in Harsh Environments. *SENSORS*, 20(1).

Xia, M., Xiu, C., Yang, D., Wang, L., 2018. A novel pdr aided uwb indoor positioning method. *2018 Ubiquitous Positioning, Indoor Navigation and Location-Based Services (UPINLBS)*, 1–7.

Yassin, Ali, N. Y. A. M., Al-Dubai, A., Liu, R., Yuen, C., Raulefs, R., Aboutanios, E., 2017. Recent Advances in Indoor Localization: A Survey on Theoretical Approaches and Applications. *IEEE Communications Surveys and Tutorials*, 19(2), 1327-1346.

Yu, K., Wen, K., Li, Y., Zhang, S., Zhang, K., 2019. A Novel NLOS Mitigation Algorithm for UWB Localization in Harsh Indoor Environments. *IEEE Transactions on Vehicular Technology*, 68(1), 686-699.

Zeakvat, M, B. R., D., D. G., 2021. An overview on position location: past, present, future. *International Journal of Wireless Information Networks*, 28(1), 47–76.

Zeng, Z., Bai, R., Wang, L., Liu, S., 2019. Nlos identification and mitigation based on cir with particle filter. *2019 IEEE Wireless Communications and Networking Conference (WCNC)*, 1–6.