

Robust and Efficient CIR-Based Outlier Rejection for Tightly Coupled UWB–ODO–Inertial Navigation

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Abstract—The ultrawideband (UWB) technology has been proven to achieve continuous absolute positioning for wheeled robots. However, its accuracy is often degraded by non-line-of-sight (NLOS) propagation in complex environments. In this article, a channel impulse response (CIR)-based method is proposed to improve the NLOS outlier rejection performance and the positioning accuracy. The proposed method is integrated into a tightly coupled UWB–odometer (ODO)–inertial navigation system, named CIR-UOINS, as an application instance. Multiple CIR feature parameters are constructed, and feature selection is performed by using probability density distributions, the Bhattacharyya distance, and the correlation analysis. Based on the selected CIR feature, a likelihood ratio test is employed to identify NLOS outliers directly at the signal level. Experiments are conducted in a semi-indoor rooftop with an area of about 1000 m². Sufficient results demonstrate that the proposed CIR-UOINS achieves a positioning accuracy of about 0.19 m in the complex scenario, which is comparable to that of the state-of-the-art (SOTA) random sample consensus (RANSAC)-based method. Moreover, the outlier rejection time is reduced by 96.2 % compared to the SOTA RANSAC-based method. Hence, CIR-UOINS achieves a better balance between the positioning accuracy and the computational efficiency.

Index Terms—Multisensor fusion, outlier rejection, probability density function (pdf), ultrawideband (UWB) channel impulse response (CIR), UWB positioning.

I. INTRODUCTION

WITH the advancement of the Internet of Things (IoT), high-accuracy positioning has become increasingly essential in various industrial scenarios [1]. Traditional wireless positioning technologies, such as Bluetooth, Wi-Fi, and radio frequency identification (RFID), are limited by their narrow bandwidths and low temporal resolutions, which lead

to poor positioning accuracy in complex environments [2]. In contrast, the ultrawideband (UWB) offers a wide bandwidth and superior temporal resolution, enabling the accurate estimation of signal propagation time. Thus, the UWB is considered a promising solution for high-accuracy positioning in complex environments. In practical deployments, however, UWB signals are frequently blocked by obstacles and disturbed by multipath effects, resulting in non-line-of-sight (NLOS) propagation [3]. These NLOS propagation conditions introduce significant ranging biases, which severely degrade positioning accuracy and reliability. Therefore, UWB range outliers need to be detected and rejected to improve positioning performance.

Conventional UWB outlier rejection methods, such as the chi-square test and the random sample consensus (RANSAC) method, are often based on range residuals or geometric constraints. However, these methods generally rely heavily on accurate pose information and sufficient valid measurements. The rejection performance of the chi-square test degrades in complex NLOS environments due to inaccurate prior state estimation. Although the RANSAC method is relatively robust, it entails high computational cost. In contrast, the channel impulse response (CIR) data can reflect multipath propagation characteristics. Therefore, line-of-sight (LOS) and NLOS channel states can be distinguished directly at the signal level and independently of pose information [4].

Hence, a CIR-based UWB outlier rejection method is proposed and integrated into an extended Kalman filter (EKF)-based UWB–odometer (ODO)–inertial navigation system, named CIR-UOINS. Specifically, probability density functions (PDFs) of the selected CIR features are first established under LOS and NLOS conditions. A likelihood ratio test is subsequently adopted to perform channel identification, followed by an innovation-based chi-square test for secondary screening. The CIR-based likelihood ratio test rejects outliers without using pose information, thereby reducing the dependence of CIR-UOINS on accurate pose estimation. The proposed method can enhance the positioning accuracy and robustness of the UWB–ODO–inertial navigation system in complex scenarios. Furthermore, the method exhibits high computational efficiency and low implementation complexity, meeting the demands of lightweight and real-time navigation systems [5]. The main contributions of this article are as follows.

- 1) Several representative feature parameters are extracted from the UWB CIR data. The discriminative capability

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and interfeature correlations are analyzed in detail. The results show that high LOS/NLOS classification accuracy can be achieved using only a single selected feature.

- 2) A CIR-based outlier rejection method is developed and integrated into an EKF-based UWB-ODO-inertial navigation system. Specifically, a likelihood ratio test is built based on CIR feature PDFs under LOS and NLOS conditions, and an innovation-based chi-square test is further employed for secondary screening of remaining outliers. This two-stage framework improves the system robustness under NLOS conditions while maintaining low computational complexity.
- 3) Quantitative experiments are conducted in a semi-indoor rooftop with an area of approximately 1000. The proposed CIR-UOINS achieves a positioning accuracy of about 0.19 m, which is comparable to that of the RANSAC-based method while substantially reducing the computational cost. Additional experiments in an underground garage environment further verify the effectiveness of the proposed method under different complex scenarios.

The remainder of this article is organized as follows. Section II reviews the related work on UWB outlier rejection methods. Section III presents the system overview of the proposed CIR-UOINS. The proposed CIR-based outlier rejection method is described in Section IV. Section V presents the tightly coupled UWB-ODO-inertial fusion framework. Experimental results are reported and discussed in Section VI. Finally, Section VII concludes this article.

II. RELATED WORK

UWB can achieve high positioning accuracy in LOS scenarios, but it is prone to NLOS propagation in complex environments, which degrades positioning reliability. Hence, range outliers need to be detected and rejected. Existing UWB outlier rejection methods can be broadly categorized into range- and CIR-based methods.

A. Range-Based Methods

Range-based methods mitigate NLOS effects by rejecting or correcting UWB ranges, which can be categorized into single-epoch and multiepoch methods based on the utilization of temporal information. Single-epoch methods detect outliers using only current ranges, typically based on range residuals or geometric constraints. Chan et al. [6] and Hua et al. [7] identified outliers by comparing positioning results obtained from different anchor combinations at the same epoch. Zhao et al. [8] introduced known baseline constraints and differenced ranges from different anchors to reduce the influence of measurements with large residuals. In [9], UWB ranges were predicted using visual displacement increments, and outliers were detected based on prediction errors. In [10], range bias parameters were incorporated into the positioning model and jointly estimated with position states to mitigate NLOS. However, since only current measurements are used, single-epoch methods often lack robustness under persistent NLOS conditions or when reliable measurements are limited.

Multiepoch methods enhance outlier rejection robustness by exploiting temporal information. In [11], current ranges were predicted using historical measurements, and outliers were detected based on prediction errors. Nevertheless, separate modeling and recursive estimation are required for each anchor, resulting in high complexity. Sun et al. [12] employed a support vector machine (SVM) to detect candidate NLOS measurements from UWB ranging information and then identified NLOS conditions using a triangle-rule consistency check. The two-stage rejection process increases the implementation complexity. Cheng et al. [13] evaluated the outlier severity by analyzing the consistency of the positioning results across consecutive epochs and subsequently applied different filtering strategies to suppress NLOS. This method involves measurement grouping and multimodel fusion, which imposes a heavy computational burden. In [14] and [15], a multistate constraint Kalman filter (MSCKF) was used to jointly optimize historical states, while RANSAC was adopted to verify the consistency of UWB ranges for outlier detection and rejection. However, both MSCKF and RANSAC typically incur high computational cost, limiting their real-time deployment.

Overall, single-epoch outlier rejection methods are simple and thus less robust under persistent NLOS conditions. Multiepoch methods can improve outlier rejection robustness but often incur higher computational cost, limiting their applicability in real-time systems.

B. CIR-Based Methods

Compared with range-based methods, CIR-based methods can achieve signal-level outlier rejection by using CIR data. In [16], the raw CIR data were input into a convolutional neural network-long short-term memory (CNN-LSTM) model, in which structural features were extracted by the CNN and temporal correlations were modeled by the LSTM for LOS/NLOS classification. In [17], the CIR data were processed by a fully convolutional network with self-attention for propagation-state classification. In [18], a channel attention module was introduced into a CNN to adaptively weight CIR feature channels and improve the classification accuracy. In [19], a CNN was trained using the raw CIR data to simultaneously perform LOS/NLOS classification and ranging error regression, enabling error compensation. In addition to methods that directly process the time-domain CIR data, approaches based on CIR transformations have also been investigated. For example, Wang et al. [20] transformed the CIR data into 2-D images using 1-D wavelet packet decomposition and subsequently employed a CNN for channel classification. Deng et al. [21] converted the CIR data into Gramian angular field images and designed a parallel deep learning model for NLOS detection and error mitigation. Lv et al. [22] proposed a dual-channel network to process the time-domain CIR data and time-frequency spectrograms for NLOS identification.

Despite their classification capability, the above learning-based methods often involve network training and inference, introducing additional implementation complexity. In contrast, traditional CIR feature-based methods are generally more computationally efficient. In [23], various CIR parameters were extracted to construct a fuzzy decision tree for channel

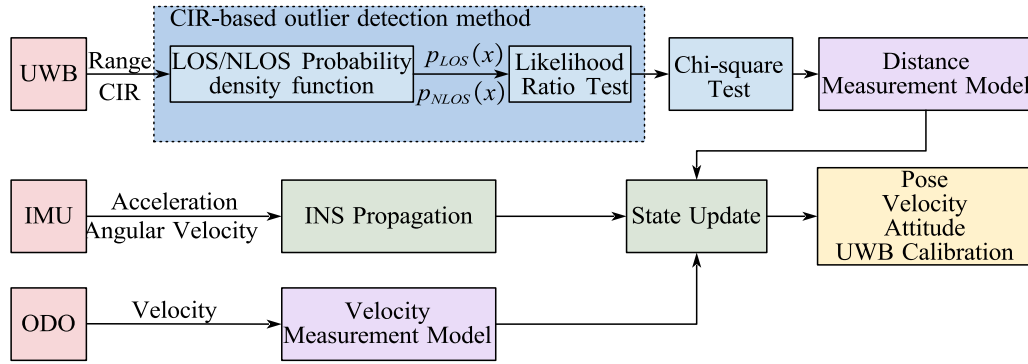


Fig. 1. System overview of the proposed CIR-UOINS.

classification. In [24], multiple CIR features were combined into a joint criterion to identify NLOS channels. However, these methods depend on empirical parameters, which restricts their adaptability in complex environments. Wu et al. [25] developed a fuzzy inference system using CIR parameters for ranging error correction. This approach exhibits limited effectiveness against significant outliers, as it mainly smooths ranging errors. Schroeder and Haefner [26] predicted obstruction risks using temporal CIR variations and reduced the influence of unreliable ranges. Since this method requires continuous observations, it is less suitable for static NLOS scenarios. In [27], multipath statistics were used in a likelihood ratio test for LOS/NLOS classification. Nevertheless, the performance of this method hinges on accurate multipath estimation and is prone to bias in severe NLOS environments. In [28], multiple CIR statistics were employed in likelihood ratio and hypothesis tests, but the required covariance-based parameter estimation incurs high computational complexity.

In summary, CIR-based methods enable signal-level outlier rejection. Among these approaches, learning-based methods often involve complex models. Traditional feature-based methods are more efficient, but many of them still depend on empirical parameters or additional processing.

III. SYSTEM OVERVIEW

As shown in Fig. 1, a CIR-based outlier rejection method is developed and integrated into a tightly coupled UWB-ODO-inertial navigation system. The prior state and the covariance at the current epoch are obtained through the INS propagation. ODO observations are utilized to construct the velocity measurement model, thereby suppressing the IMU error accumulation during the state update. For UWB measurements, outlier rejection is first performed using the CIR information. Feature parameters are extracted from the CIR data, and their PDFs are established under both LOS and NLOS conditions. The channel state for each CIR sample is then identified via a likelihood ratio test, which effectively detects NLOS range outliers. Subsequently, an innovation-based chi-square test is adopted for secondary screening, and only the retained ranges are used for the state update. Finally, the UWB range residuals and ODO velocity residuals are fused to update the system state and the covariance. The posterior estimates of the position, velocity, attitude, and UWB

calibration parameters are then obtained and fed back for the INS propagation at the next epoch.

IV. CIR-BASED OUTLIER REJECTION FOR UWB RANGES

The UWB CIR exhibits distinct characteristics under LOS and NLOS conditions. Therefore, statistical features can be extracted to facilitate channel state identification. Given that candidate features possess varying discriminative capabilities, a detailed feature analysis and selection process is conducted to enhance the classification performance. This section first characterizes the CIR waveforms under LOS and NLOS conditions. Subsequently, the statistical features are defined, and an optimal feature set is selected leveraging PDFs, Bhattacharyya distances, and the correlation analysis. Finally, a likelihood ratio test is introduced to identify NLOS ranges.

A. CIR Under LOS and NLOS Conditions

A UWB module based on the Decawave DW1000 chip, which complies with the IEEE 802.15.4-2011 UWB standard, is used in this article. With a time measurement resolution of 15.65 ps, the chip achieves centimeter-level ranging accuracy [29]. It allows the extraction of the accumulated CIR stored in its on-chip registers. At a pulse repetition frequency of 64 MHz, the acquired CIR consists of 1016 complex sampling points [29]. The amplitude sequence can be obtained by calculating the magnitude of each complex sampling point. The measured CIR under LOS and NLOS conditions is shown in Fig. 2, where the horizontal and vertical axes represent the sampling-point index and amplitude, respectively. Given that the first path in the CIR output of the DW1000 typically appears near index 750 [30], a window of 400 sampling points from indices 601 to 1000 is extracted for analysis. This window encompasses the first path and subsequent multipath components, effectively minimizing data redundancy.

As shown in Fig. 2, no obstructions exist between the base station and the tag under LOS conditions. The direct path signal is typically the strongest. Therefore, the first peak is also the highest, with an amplitude significantly larger than that of subsequent multipath components. In this case, the arrival time of the direct path can be determined more accurately, enabling high-accuracy ranging and positioning. Under NLOS conditions, obstructions exist between the base

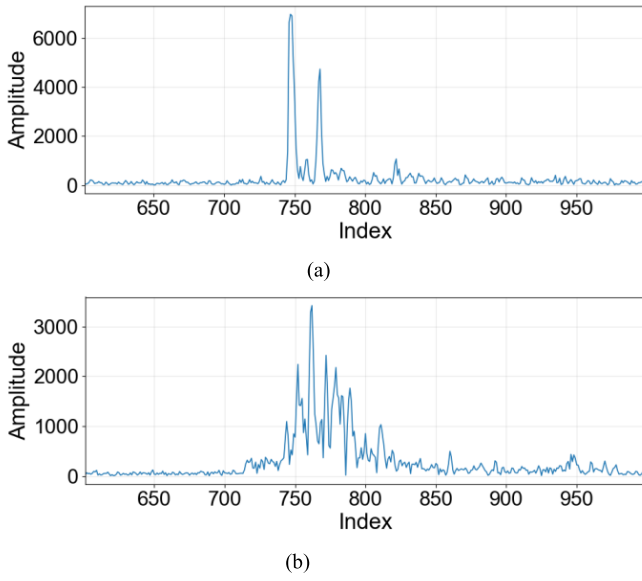


Fig. 2. CIR under (a) LOS and (b) NLOS conditions.

station and the tag. The direct path signal is attenuated or even blocked, while some reflected paths may exhibit higher amplitudes, rendering the first-peak amplitude lower than that of later reflection peaks. As a result, a reflected path may be mistakenly identified as the direct path, introducing multipath errors and degrading positioning accuracy. These differences indicate that the CIR exhibits distinct characteristics under LOS and NLOS conditions. Thus, NLOS range outliers can be identified and rejected based on the CIR, thereby improving positioning accuracy.

B. Definitions of CIR Features

The CIR features are extracted from four dimensions: energy distribution, statistical distribution, delay spread, and the relationship between the first and global peaks. Eight feature parameters are selected for analysis. Let the extracted CIR sequence be $c[n]$, $n = 0, 1, \dots, N-1$, where $c[n]$ is the amplitude of the n th sampling point and N is the sequence length. In this article, N is set to 400, corresponding to indices 601–1000 in the original CIR sequence. The definition of each feature parameter is shown in Table I, where the global peak is defined as the peak with the maximum amplitude among all detected peaks in the CIR sequence. A detected peak is defined as a local maximum with an amplitude exceeding $\mu_{\text{noise}} + 12\sigma_{\text{noise}}$, where μ_{noise} and σ_{noise} are the noise mean and standard deviation estimated from the first 50 sampling points of each CIR sequence, respectively. A detailed description of each feature is as follows.

1) *fp_ratio*: The *fp_ratio* is defined as

$$\beta_{fp} = \frac{c[n_{fp}]}{\sum_{k \in \zeta} c[k]} \quad (1)$$

where n_{fp} is the sampling-point index of the first peak and ζ denotes the set of detected peak indices. Under LOS conditions, the direct path dominates, leading to a large β_{fp} . Under NLOS conditions, the direct path is obstructed, and later

Category	Name	Description
Energy features	<i>fp_ratio</i>	Relative amplitude proportion of the first peak to the sum of all detected peaks.
	<i>mp_ratio</i>	Relative amplitude proportion of the global peak to the sum of all detected peaks.
Peak-related features	<i>fm_ratio</i>	Amplitude ratio of the first peak to the global peak.
	<i>peak_gap</i>	Index difference between the first peak and the global peak.
Statistical distribution features	<i>amp_skew</i>	Skewness of the CIR amplitude distribution [28].
	<i>amp_kurt</i>	Kurtosis of the CIR amplitude distribution [28].
Delay-spread features	<i>delay_mean</i>	Power-weighted mean delay over sampling-point indices [24].
	<i>delay_rms</i>	Root-mean-square delay spread over sampling-point indices [24].

reflected components become more prominent, resulting in a small β_{fp} .

2) *mp_ratio*: The *mp_ratio* is defined as

$$\beta_{mp} = \frac{c[n_{mp}]}{\sum_{k \in \zeta} c[k]} \quad (2)$$

where n_{mp} is the sampling-point index of the global peak. Under LOS conditions, the global peak usually corresponds to the direct path, leading to a large β_{mp} . Under NLOS conditions, multipath components become more complex, and β_{mp} is consequently reduced.

3) *fm_ratio*: The *fm_ratio* is defined as

$$\beta_{fm} = \frac{c[n_{fp}]}{c[n_{mp}]} \quad (3)$$

Under LOS conditions, the direct path is typically the earliest and strongest arrival. Thus, the first and global peaks exhibit similar amplitudes, leading to a large β_{fm} . Under NLOS conditions, the direct path is obstructed, and larger peaks often appear in later reflected paths. Therefore, β_{fm} is usually small.

4) *peak_gap*: The *peak_gap* is defined as

$$\Delta n = |n_{mp} - n_{fp}| \quad (4)$$

Under LOS conditions, the first and global peaks are located at the same or adjacent indices, resulting in a small Δn . Under NLOS conditions, stronger peaks often appear in subsequent reflected paths, leading to a larger value of Δn .

5) *amp_skew*: The *amp_skew* is defined as

$$\gamma = \frac{1}{N} \sum_{n=0}^{N-1} \left(\frac{c[n] - \mu}{\sigma} \right)^3 \quad (5)$$

where μ and σ are the mean and standard deviation of the amplitude sequence, respectively. Under LOS conditions, high amplitudes are concentrated in a few sampling points, leading to a large γ . Under NLOS conditions, richer multipath components flatten the amplitude distribution, resulting in a small γ .

6) *amp_kurt*: The *amp_kurt* is defined as

$$\kappa = \frac{1}{N} \sum_{n=0}^{N-1} \left(\frac{c[n] - \mu}{\sigma} \right)^4. \quad (6)$$

Under LOS conditions, the CIR exhibits a distinct peak structure, leading to a large κ . Under NLOS conditions, the amplitude distribution becomes flatter, generally resulting in a smaller κ .

7) *delay_mean*: The *delay_mean* is defined as

$$\tau_{\text{mean}} = \frac{\sum_{n=0}^{N-1} n |c[n]|^2}{\sum_{n=0}^{N-1} |c[n]|^2} \quad (7)$$

where n is the sampling-point index, representing the relative delay position since the sampling interval is fixed. $|c[n]|^2$ denotes the CIR power at the n th sampling point. Under LOS conditions, power is concentrated in the early arriving direct path, leading to a small τ_{mean} . Under NLOS conditions, power is distributed over delayed reflected and scattered components, and τ_{mean} is usually large.

8) *delay_rms*: The *delay_rms* is defined as

$$\tau_{\text{rms}} = \sqrt{\frac{\sum_{n=0}^{N-1} (n - \tau_{\text{mean}})^2 |c[n]|^2}{\sum_{n=0}^{N-1} |c[n]|^2}}. \quad (8)$$

Under LOS conditions, power is more concentrated, resulting in a small τ_{rms} . Under NLOS conditions, richer multipath components disperse power over a wider delay range, leading to large τ_{rms} .

C. Analysis and Selection of CIR Features

1) *Feature Probability Densities*: Kernel density estimation is used to model the feature PDFs. The observations of the feature x are denoted by $\{x_1, x_2, \dots, x_M\}$, where M is the number of samples and x_i is the feature value of the i th sample. The pdf of this feature is estimated by

$$\begin{aligned} p(x) &= \frac{1}{Nh} \sum_{i=1}^M K\left(\frac{x - x_i}{h}\right) \\ &= \frac{1}{Nh} \sum_{i=1}^M \frac{1}{\sqrt{2\pi}} \exp\left[-\frac{1}{2} \left(\frac{x - x_i}{h}\right)^2\right] \end{aligned} \quad (9)$$

where $K(\cdot)$ is the kernel function, with a Gaussian kernel employed in this article. h is the bandwidth parameter. If h is too small, the estimation result is sensitive to noise. If h is too large, the curve becomes overly smooth, resulting in the loss of details. Scott's rule [31] is used to adaptively select h , balancing stability and resolution.

To establish the feature distributions under LOS and NLOS conditions, the corresponding CIR datasets were collected. Both datasets were obtained during dynamic robot motion. During the LOS data collection, the direct paths between the tag and the six base stations were kept unobstructed. Conversely, during the NLOS data collection, the base stations were placed behind obstacles, thereby blocking the direct paths between the tag and all base stations. For each propagation scenario, 3000 CIR samples were collected from every base station. Subsequently, utilizing these datasets, kernel density

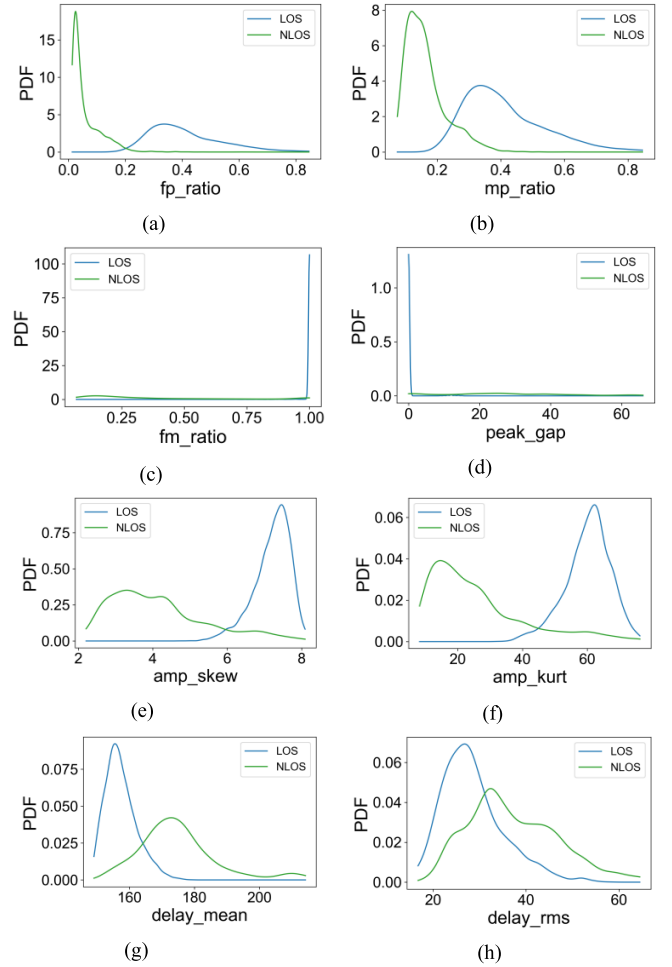


Fig. 3. PDFs of CIR features. (a) *fp_ratio*, (b) *mp_ratio*, (c) *fm_ratio*, (d) *peak_gap*, (e) *amp_skew*, (f) *amp_kurt*, (g) *delay_mean*, and (h) *delay_rms*.

estimation was performed for each feature. The PDFs for both scenarios, $p_{\text{LOS}}(x)$ and $p_{\text{NLOS}}(x)$, were then obtained. The discriminative ability of each feature was evaluated by comparing the location, shape, and overlap of the two distributions. Larger distributional differences and smaller overlaps indicate a stronger discriminative ability.

The PDFs of the features under LOS and NLOS conditions are shown in Fig. 3. It is observed that the distributions of *fp_ratio*, *fm_ratio*, and *peak_gap* are clearly separated under the two conditions with minimal overlap, indicating strong discriminative ability. In contrast, greater overlap is observed for *amp_skew*, *amp_kurt*, and *mp_ratio*, suggesting the reduced discriminative ability. Furthermore, the most severe overlap is exhibited by the distributions of *delay_mean* and *delay_rms*, demonstrating the weakest discriminative ability.

2) *Discriminative Ability*: To quantify the LOS/NLOS discriminative ability of each feature, the Bhattacharyya distance [32] is used to measure the overlap between the two distributions. For feature x , the distance is defined as

$$D_B = -\ln \left(\int \sqrt{p_{\text{LOS}}(x) p_{\text{NLOS}}(x)} dx \right) \quad (10)$$

where the integral term is referred to as the Bhattacharyya coefficient. When the two distributions completely overlap,

TABLE II
BHATTACHARYYA DISTANCES OF THE CIR FEATURES

Feature	Bhattacharyya distance
fp_ratio	2.1509
fm_ratio	2.1124
peak_gap	2.0412
amp_skew	1.0944
mp_ratio	1.0199
amp_kurt	0.9772
delay_mean	0.6008
delay_rms	0.1480

this coefficient equals 1, corresponding to $D_B = 0$. When the two distributions are completely disjoint, the coefficient approaches 0, leading to a large D_B . Therefore, a larger D_B indicates a smaller distribution overlap and a stronger discriminative ability.

The Bhattacharyya distances of the features are shown in Table II. The distances of fp_ratio, fm_ratio, and peak_gap are significantly larger than those of the other features, indicating a stronger LOS/NLOS classification ability. This result is consistent with the pdf curves. Therefore, these three features are selected to construct the likelihood ratio test.

3) *Feature Correlation Analysis*: Highly correlated features usually contain redundant information. Therefore, feature correlations should be further analyzed after the individual discriminative ability is evaluated. The Pearson correlation coefficient [33] is used to measure the linear correlations between the features. For features x and y , the coefficient is computed as

$$\rho_{xy} = \frac{\sum_{i=1}^N (x_i - \bar{x})(y_i - \bar{y})}{\sqrt{\sum_{i=1}^N (x_i - \bar{x})^2 \sum_{i=1}^N (y_i - \bar{y})^2}} \quad (11)$$

where x_i and y_i are the i th sample values of features x and y , respectively. $\bar{x}$ and $\bar{y}$ are the corresponding sample means, and N is the total number of samples. The correlation coefficient lies in the range $\rho_{xy} \in [-1, 1]$. A larger absolute value of the coefficient indicates a stronger linear correlation, whereas a value closer to 0 indicates a weaker correlation.

The correlation coefficients among the features are shown in Fig. 4. Among the three selected features, no feature pair exhibits consistently strong linear correlation under both the LOS and NLOS conditions. Specifically, while fp_ratio and fm_ratio exhibit strong correlation under the NLOS condition, their correlation is weak under the LOS condition. The correlation between fm_ratio and peak_gap is moderate under the LOS condition but weakens under the NLOS condition. fp_ratio and peak_gap remain weakly correlated under both conditions. Therefore, the selected features have low redundancy and can be jointly used for the LOS/NLOS classification.

D. NLOS Identification

CIR features can be utilized for channel state classification with fixed thresholds. However, fixed-threshold-based

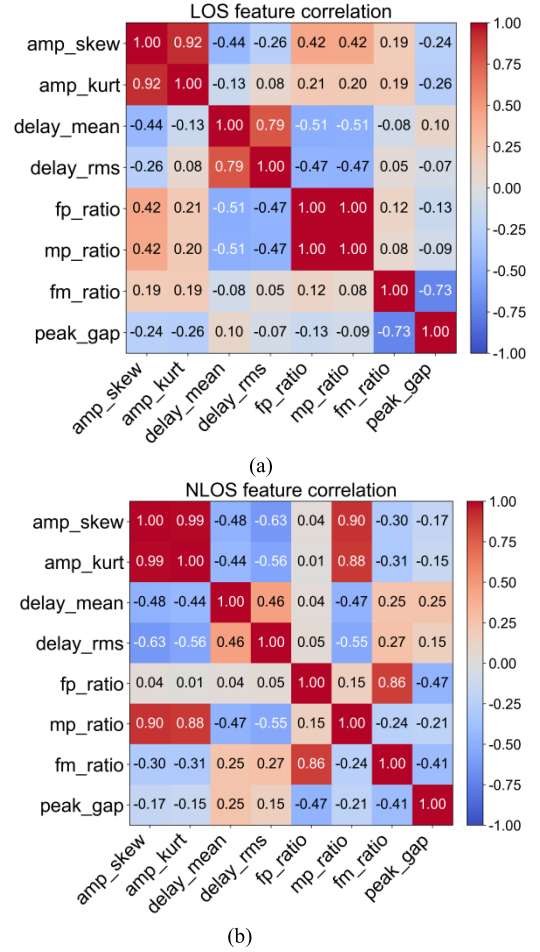


Fig. 4. Heatmap of correlation coefficients among CIR features. (a) LOS. (b) NLOS.

decisions exhibit limited reliability. Therefore, the LOS/NLOS classification is formulated as a binary hypothesis test

$$\begin{cases} H_0 : \text{LOS} \\ H_1 : \text{NLOS} \end{cases} \quad (12)$$

where H_0 and H_1 are the null and alternative hypotheses, indicating that a given sample corresponds to LOS and NLOS propagation, respectively. The likelihood ratio test statistic is constructed as

$$\lambda(x) = \frac{p_{\text{LOS}}(x)}{p_{\text{NLOS}}(x)}. \quad (13)$$

The decision rule is given by

$$\lambda(x) \underset{H_1}{\overset{H_0}{\geq}} 1. \quad (14)$$

Specifically, a sample is classified as LOS when $\lambda(x) \geq 1$; otherwise, it is classified as NLOS. According to the correlation analysis, the three selected features can be assumed to be approximately independent. Thus, the likelihood ratio statistic for joint multifeature classification is given by

$$\lambda(x_1, x_2 \dots x_k) = \frac{p_{\text{LOS}}(x_1)}{p_{\text{NLOS}}(x_1)} \times \frac{p_{\text{LOS}}(x_2)}{p_{\text{NLOS}}(x_2)} \dots \times \frac{p_{\text{LOS}}(x_k)}{p_{\text{NLOS}}(x_k)} \quad (15)$$

TABLE III
 NLOS IDENTIFICATION PERFORMANCE

Feature Combination	Accuracy	Precision	Recall
fp_ratio	0.979	0.991	0.966
fp_ratio-peak_gap	0.945	0.980	0.911
fp_ratio-fm_ratio	0.941	0.981	0.903
fp_ratio-fm_ratio-peak_gap	0.923	0.981	0.867
fm_ratio-peak_gap	0.921	0.980	0.863
peak_gap	0.919	0.980	0.862
fm_ratio	0.918	0.981	0.860

where x_k denotes the k th feature. The corresponding decision rule is $\lambda(x_1, x_2 \dots x_k) \stackrel{H_0}{\underset{H_1}{\geq}} 1$.

The NLOS identification performance under different feature combinations is presented in Table III. In each evaluation, CIR samples from five base stations are used to estimate the LOS and NLOS PDFs, while samples from the remaining base station are used for testing. The reported metrics are averaged over six evaluations with different base stations used for testing. Accuracy represents the proportion of correctly classified samples. Precision denotes the proportion of true NLOS samples among those classified as NLOS. Recall represents the proportion of true NLOS samples that are correctly identified. The results indicate that fp_ratio achieves the highest accuracy, precision, and recall among all evaluated feature combinations. Therefore, fp_ratio is selected as the discriminative feature in this article.

V. TIGHTLY COUPLED UWB-ODO-INERTIAL FUSION

A tightly coupled UWB-ODO-inertial navigation system based on the EKF is developed in this article. The state estimation is performed by fusing UWB range measurements and ODO velocity measurements. In addition, a chi-square-test-based outlier rejection method is introduced to enhance the system robustness. In this section, the state vector is first presented, followed by the UWB and ODO measurement models. Finally, the innovation-based chi-square test is described.

A. State Vector

The state vector is composed of two parts: the IMU error states and the systematic UWB ranging error states, which are denoted as $\mathbf{X}_{IMU}$ and $\mathbf{X}_{UWB}$, respectively. The entire state vector is denoted by $\mathbf{X}$ and is defined as follows:

$$\begin{aligned} \mathbf{X} &= [\mathbf{X}_{IMU}^T \quad \mathbf{X}_{UWB}^T]^T \\ \mathbf{X}_{IMU} &= [\delta\phi_b^w \quad \delta\mathbf{p}_b^w \quad \delta\mathbf{v}_b^w \quad \delta\mathbf{b}_a \quad \delta\mathbf{b}_g]^T \\ \mathbf{X}_{UWB} &= [\delta s_{u_1}, \delta\mathbf{b}_{u_1}]^T \\ &= [\delta s_{u_1} \delta s_{u_2} \dots \delta s_{u_r}, \delta\mathbf{b}_{u_1} \delta\mathbf{b}_{u_2} \dots \delta\mathbf{b}_{u_r}]^T \end{aligned} \quad (16)$$

where b and w represent the body frame and the world frame, respectively. $\delta\phi_b^w$, $\delta\mathbf{p}_b^w$, and $\delta\mathbf{v}_b^w$ are the attitude, position, and velocity errors of the IMU, respectively. $\delta\mathbf{b}_a$ and $\delta\mathbf{b}_g$

represent the accelerometer bias errors and gyroscope bias errors, respectively. δs_{u_i} and $\delta\mathbf{b}_{u_i}$ are the scale factor error and offset error of the i th UWB base station, respectively. r denotes the number of UWB base stations in the system. Further details on the parameters in (16) are provided in [15].

B. UWB and ODO Measurement Models

The residual of the UWB range measurement model is obtained by calculating the difference between the measured distance from the UWB base station and the predicted range. For instance, the residual of the range measurement $d_{i,k}$ from the i th UWB base station at time t_k is defined as

$$\begin{aligned} \mathbf{r}_{i,k} &= s_{u_i} \cdot \|\mathbf{p}_{ant}^w - \mathbf{p}_{u_i}^w\| + b_{u_i} - d_{i,k} \\ &= s_{u_i} \cdot \|\mathbf{p}_{b_k}^w + \mathbf{R}_{b_k}^w \mathbf{p}_{ant}^b - \mathbf{p}_{u_i}^w\| + b_{u_i} - d_{i,k} \end{aligned} \quad (17)$$

where s_{u_i} and b_{u_i} are the scale factor and offset of the i th UWB base station, respectively; $\mathbf{p}_{ant}^w$ and $\mathbf{p}_{ant}^b$ are the positions of the UWB antenna in the w frame and the b frame, respectively; $\mathbf{p}_{b_k}^w$ and $\mathbf{R}_{b_k}^w$ are the position and attitude of the IMU in the w frame at time t_k , respectively; and $\mathbf{p}_{u_i}^w$ is the position of the i th UWB base station in the w frame.

In the ODO measurement model, the velocity residual is defined as the difference between the ODO-measured and estimated robot velocity

$$\mathbf{r}_{odo} = \mathbf{R}_b^w \mathbf{R}_v^b \mathbf{v}_{odo} - (\mathbf{v}_b^w - \mathbf{R}_b^w [\mathbf{l}_{odo} \times \boldsymbol{\omega}^b]) \quad (18)$$

where $\mathbf{R}_b^w$ is the direction cosine matrix between the b frame and the vehicle frame, $\mathbf{v}_{odo}$ is the velocity measured by the ODO, and $\mathbf{v}_b^w$ is the velocity estimated by the IMU. $\mathbf{l}_{odo}$ is the lever arm vector from the IMU to the ODO, $\boldsymbol{\omega}^b$ is the current angular velocity of the IMU, and $\times$ represents the cross product operator. Further details on the parameters in (17) and (18) are provided in [15].

C. Innovation-Based Chi-Square Test

In some scenarios, the CIR-based outlier rejection method may generate channel state decisions that are inconsistent with the true channel state. This occurs because the reflected and direct paths may merge into a single peak in the CIR when their propagation delays are sufficiently close. As a result, a true NLOS signal may exhibit LOS-like characteristics. An LOS-like CIR obtained under the NLOS condition is shown in Fig. 5. Although only one dominant peak is observed, the peak is wider and exhibits a longer trailing edge than that observed under the LOS condition, indicating overlap between the reflected and direct paths in the CIR. Therefore, certain limitations exist in LOS/NLOS classification based solely on the CIR features. To improve the reliability of outlier rejection, an innovation-based chi-square test is employed as a secondary screening step after the CIR-based outlier rejection.

First, the UWB range residual is used as the innovation, as defined in (17). The innovation covariance is given by

$$\mathbf{C}_{i,j} = \mathbf{H}\mathbf{P}\mathbf{H}^T + \mathbf{R}_{i,j} \quad (19)$$

where $\mathbf{H}$ and $\mathbf{P}$ are the Jacobian matrix and the covariance matrix of the state vector, respectively. $\mathbf{R}_{i,j}$ is the observation

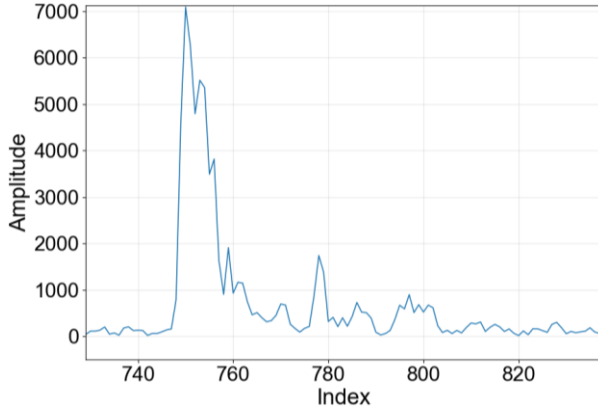


Fig. 5. LOS-like CIR in an NLOS channel.

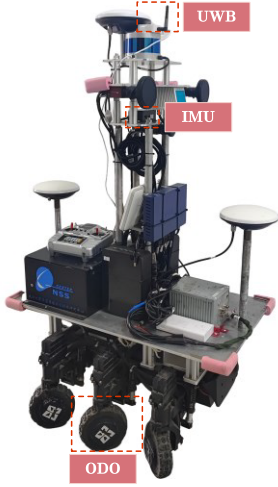


Fig. 6. Employed wheeled robot for real-world experiments.

noise covariance of the j th range from the i th UWB base station. The normalized innovation is then given by

$$y_{i,j} = \frac{r_{i,j}}{\sqrt{C_{i,j}}}. \quad (20)$$

Finally, $y_{i,j}$ is compared with a preset chi-square threshold. If the threshold is exceeded, the corresponding range is identified as an outlier and rejected. Otherwise, the range is retained as a valid measurement.

VI. EXPERIMENTS AND ANALYSIS

A. Experimental Setup

A wheeled robot is used for quantitative experiments, as shown in Fig. 6. The UWB module used is LD-150, which is based on the DW1000 chip and operates at a frequency of 5 Hz. The employed IMU is ADIS16465 from ADI, with a frequency of 200 Hz. The ODO velocity is obtained from the wheel encoder of the robot chassis, with a frequency of 5 Hz. The ground-truth poses are obtained through global navigation satellite system (GNSS)/INS integrated navigation software using data from a real-time kinematic (RTK) receiver and a high-accuracy IMU.

The experimental environment is shown in Fig. 7, including the floor plan in Fig. 7(a) and the left and right views in

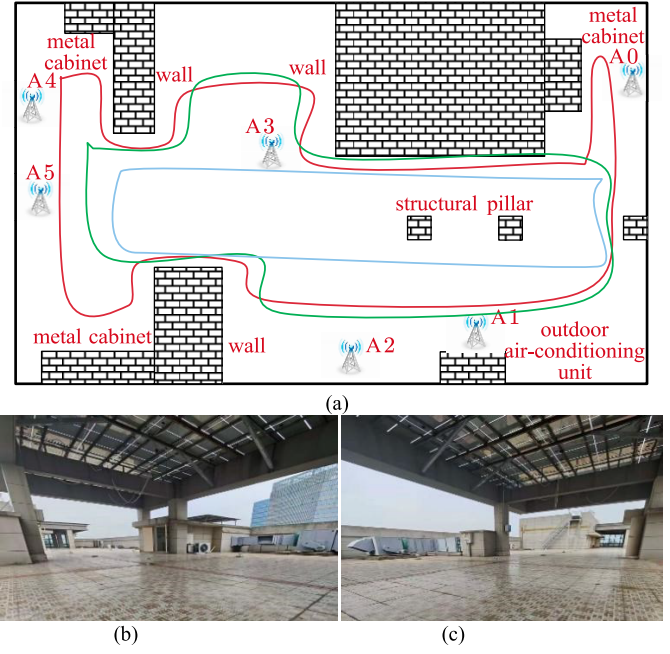


Fig. 7. Experimental environments. (a) Floor plan of the experimental environment. (b) Left view. (c) Right view.

Fig. 7(b) and (c). The site is a semi-indoor rooftop area that includes both open-sky regions and solar-panel-shaded regions. Various obstacles, such as walls, pillars, and metal cabinets, are present in the scene. Therefore, this area constitutes a typical environment with complex NLOS conditions. Six base stations are deployed at different locations on the rooftop to provide full coverage.

To evaluate the performance of the proposed CIR-UOINS under different scenarios, three motion routes are designed, as shown in Fig. 7(a). The blue and green routes are mainly located in open areas, where two or more base stations can be observed most of the time. These two routes are defined as the simple scenario since sufficient measurement constraints are available. In contrast, the red route is more affected by obstructions, and only one base station can be observed for a relatively long period. Therefore, the red route is defined as the complex scenario due to fewer available measurements and more severe signal obstructions.

The positioning accuracy is evaluated by comparing the estimated horizontal positioning results with the ground truth. The root-mean-square error (RMSE) and 95 % circular error probable (CEP95) are used as the main metrics. The configurations of different methods are shown in Table IV.

B. Evaluation of Accuracy

Tests are conducted separately using six and four base stations. When four base stations are used, base stations A1 and A4 in Fig. 7(a) are removed. The simple-scenario test sequences are denoted as simple-01, simple-02, and simple-03. Simple-01 and simple-02 follow the blue trajectory in Fig. 7(a), and simple-03 follows the green trajectory. The complex-scenario sequences are denoted as complex-01, complex-02, and complex-03, all following the red trajectory in Fig. 7(a).

TABLE IV
CONFIGURATIONS OF DIFFERENT METHODS

Method	Outlier-rejection Method	Sensor Configuration
MODR-UOINS [15]	RANSAC-based method	UWB+IMU+ODO
CHI-UOINS	Chi-square-based method	UWB+IMU+ODO
CIR-UINS	Proposed CIR-based method	UWB+IMU
CIR-UOINS-NCHI	Proposed CIR-based method without innovation-based chi-square test	UWB+IMU+ODO
CIR-UOINS	Proposed CIR-based method	UWB+IMU+ODO

TABLE V
POSITIONING ERRORS USING SIX BASE STATIONS

Error (m)	MODR-UOINS		CHI-UOINS		CIR-UOINS	
	RMSE	CEP95	RMSE	CEP95	RMSE	CEP95
Simple Scenario						
simple-01	0.13	0.24	0.13	0.25	0.13	0.24
simple-02	0.11	0.20	0.13	0.23	0.12	0.23
simple-03	0.09	0.17	0.12	0.23	0.10	0.19
RMS	0.11	0.20	0.13	0.23	0.12	0.22
Complex Scenario						
complex-01	0.14	0.24	0.26	0.51	0.15	0.28
complex-02	0.17	0.32	0.23	0.45	0.17	0.33
complex-03	0.16	0.30	0.22	0.41	0.17	0.32
RMS	0.16	0.29	0.24	0.46	0.16	0.31

1) *Using Six Base Stations:* When six base stations are used, the RMSE and CEP95 of the positioning errors are shown in Table V. In the simple scenario, only small differences are observed among the methods. This is because two or more base stations can be observed simultaneously most of the time, resulting in sufficient measurement constraints and relatively weak NLOS effects. Consequently, the impact of outliers on the overall positioning accuracy is limited.

In the complex scenario, only one base station can be observed for a relatively long period, resulting in fewer available ranges and more severe NLOS effects. Compared with CHI-UOINS, the RMSE and CEP95 of CIR-UOINS are reduced by about 33.3 % and 32.6 %, respectively, and its accuracy is comparable to that of MODR-UOINS. This indicates that the proposed CIR-based outlier rejection method can still effectively identify outliers and maintain strong robustness under complex NLOS conditions. This is because it detects outliers directly using the UWB CIR data and depends less on the pose information. In contrast, the chi-square test mainly relies on range residual statistics. When available ranges are insufficient, the absolute pose accuracy deteriorates, making the residual statistics less reliable and increasing the risk of missed outliers.

2) *Using Four Base Stations:* To further evaluate the positioning performance with fewer base stations, tests are conducted using four base stations. The results are shown in

TABLE VI
POSITIONING ERRORS USING FOUR BASE STATIONS

Error (m)	CIR-UOINS-NCHI		CIR-UINS		MODR-UOINS		CHI-UOINS		CIR-UOINS	
	RMSE	CEP95	RMSE	CEP95	RMSE	CEP95	RMSE	CEP95	RMSE	CEP95
Simple Scenario										
simple-01	0.36	0.77	0.13	0.24	0.14	0.25	0.15	0.30	0.14	0.26
simple-02	0.41	0.65	0.15	0.27	0.12	0.23	0.17	0.34	0.13	0.23
simple-03	0.51	1.06	0.12	0.23	0.10	0.18	0.14	0.25	0.11	0.20
RMS	0.43	0.84	0.13	0.25	0.12	0.22	0.15	0.30	0.13	0.23
Complex Scenario										
complex-01	0.59	1.12	0.21	0.44	0.19	0.37	0.33	0.59	0.19	0.40
complex-02	0.45	0.78	0.21	0.38	0.20	0.33	0.28	0.55	0.20	0.37
complex-03	0.49	0.88	0.19	0.37	0.17	0.30	0.28	0.53	0.19	0.36
RMS	0.51	0.94	0.20	0.40	0.18	0.33	0.30	0.56	0.19	0.37

CIR-UINS is used for comparison with CIR-UOINS to evaluate the effect of ODO measurements on positioning errors. The detailed analysis is provided in Section VI.D.3). CIR-UOINS-NCHI is used to evaluate the effect of the innovation-based chi-square test on positioning errors. The detailed analysis is provided in Section VI.D.4).

Table VI. In the simple scenario, only a slight accuracy degradation is observed across all methods. Compared with the case using six base stations, the RMSE and CEP95 of CIR-UOINS increase by only 8.3 % and 4.5 %, respectively, with accuracy remaining comparable to MODR-UOINS. This indicates that four base stations can provide sufficient geometric constraints in the simple scenario, and using six base stations provides only limited additional accuracy improvement.

In the complex scenario, compared with the case using six base stations, the RMSE and CEP95 of CIR-UOINS increase by 18.8 % and 19.4 %, respectively, and remain comparable to MODR-UOINS. This suggests that CIR-UOINS can still maintain robust positioning performance with only four base stations. Compared with CHI-UOINS, CIR-UOINS achieves RMSE and CEP95 reductions of approximately 36.7 % and 33.9 %, respectively. These reductions exceed those with six base stations, indicating that the positioning performance of CHI-UOINS degrades more significantly as the number of base stations decreases. This occurs because CHI-UOINS relies on residual-based statistical testing and requires accurate absolute poses, making it more sensitive to reduced range availability. In contrast, CIR-UOINS identifies outliers directly using the CIR data and is therefore less dependent on the number of available ranges. Hence, CIR-UOINS can still remain robust when fewer base stations are used.

Fig. 8 compares the positioning performance of different methods on the complex-01 sequence: (a) the cumulative distribution function (cdf) of positioning errors, (b) the corresponding time-series positioning error curves, and (c) the estimated trajectories. Fig. 8(b) shows that CHI-UOINS exhibits the largest error fluctuations and more pronounced error peaks, indicating the weakest outlier rejection

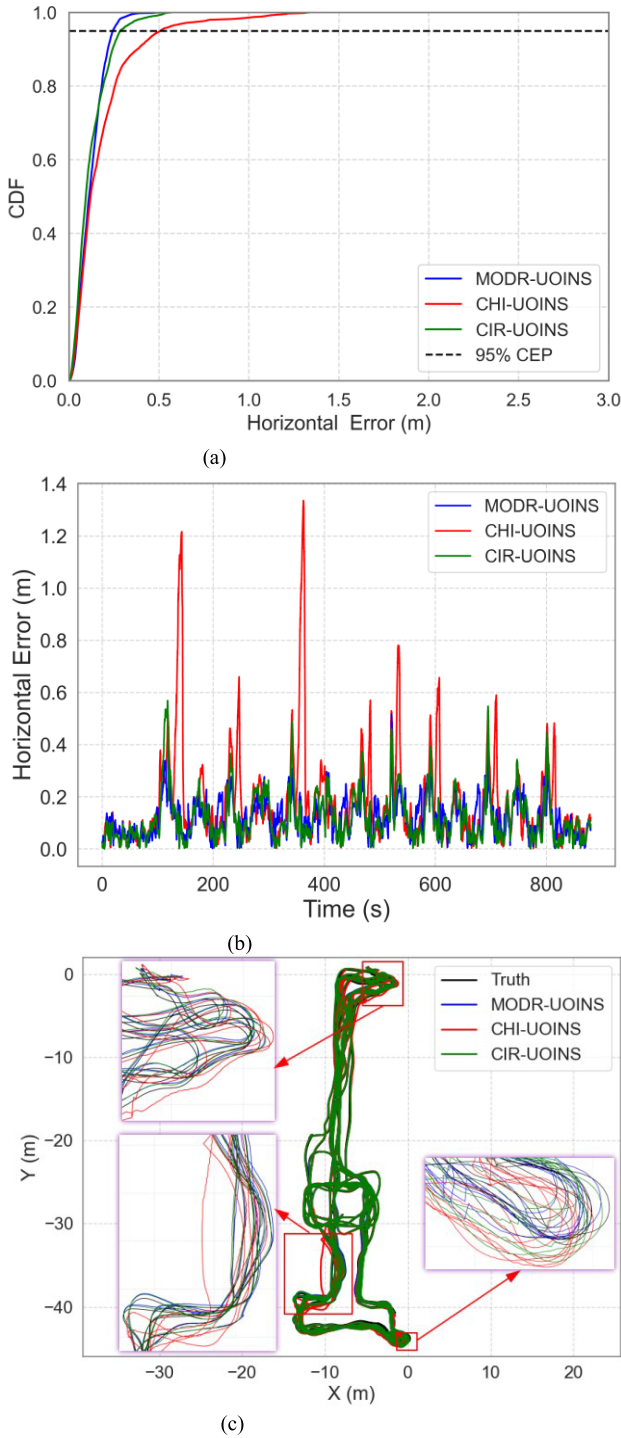


Fig. 8. Positioning errors on the complex-01 sequence. (a) CDFs of positioning error. (b) Positioning error. (c) Estimated trajectories.

capability. In contrast, smoother error curves are obtained with MODR-UOINS and CIR-UOINS. The cdf results also show that MODR-UOINS achieves the highest accuracy, followed closely by CIR-UOINS, and both methods clearly outperform CHI-UOINS. These results are consistent with Table VI. Fig. 8(c) further shows that CHI-UOINS exhibits larger deviations from the ground-truth trajectory in turning regions and heavily obstructed areas, whereas CIR-UOINS and

TABLE VII
EFFICIENCY RESULTS OF DIFFERENT METHODS

Outlier-rejection Time (ms)	MODR-UOINS	CHI-UOINS	CIR-UOINS
simple-01	29.414	0.003	1.031
simple-02	28.847	0.003	1.047
simple-03	28.415	0.002	1.05
complex-01	23.143	0.002	0.928
complex-02	23.674	0.002	0.993
complex-03	23.495	0.002	0.964
average	26.165	0.002	1.002

MODR-UOINS remain closer to the ground-truth trajectory. All three subfigures consistently show that CHI-UOINS has weaker outlier rejection capability in complex NLOS environments. In contrast, CIR-UOINS achieves performance close to that of MODR-UOINS, demonstrating strong robustness.

In summary, the proposed CIR-UOINS can still effectively suppress NLOS and maintain the high positioning accuracy when four base stations are used. Therefore, four base stations are considered sufficient for positioning in the experimental area, which helps reduce deployment costs. Accordingly, the following efficiency evaluation and ablation experiments are conducted using four base stations.

C. Evaluation of Efficiency

The outlier rejection times of different methods are listed in Table VII. CHI-UOINS achieves the shortest rejection time. CIR-UOINS has a longer rejection time than CHI-UOINS but a significantly shorter one than MODR-UOINS. Specifically, CIR-UOINS reduces the rejection time by 96.2 % compared with MODR-UOINS. Overall, although MODR-UOINS achieves the highest positioning accuracy, its real-time deployment is limited by the high computational cost. CHI-UOINS is computationally efficient, but its positioning accuracy degrades in complex NLOS environments. CIR-UOINS maintains the high positioning accuracy with low computational cost, achieving a better balance between the accuracy and the efficiency. Therefore, CIR-UOINS is more suitable for practical applications requiring both real-time performance and robustness.

D. Ablation Experiments

1) *Impact of Different Feature Combinations:* To further validate the effectiveness of the feature selection strategy, single-feature, two-feature, and three-feature combinations are constructed using the three features selected in Section IV-C2) (i.e., fp_ratio , fm_ratio , and $peak_gap$). The combinations are denoted as F1–F7, as shown in Table VIII.

The positioning errors under different feature combinations are shown in Table IX. The results indicate that satisfactory positioning accuracy can be achieved using only fp_ratio . Multifeature combinations provide no obvious improvement in the positioning accuracy. This suggests that fp_ratio is sufficient to characterize LOS/NLOS propagation conditions and can effectively identify NLOS range outliers. The result

TABLE VIII
FEATURE COMBINATIONS AND THEIR LABELS

Feature Combination	Label
fp_ratio	F1
fm_ratio	F2
peak_gap	F3
fp_ratio-fm_ratio	F4
fp_ratio-peak_gap	F5
fm_ratio-peak_gap	F6
fp_ratio-fm_ratio-peak_gap	F7

TABLE IX
POSITION RMSES UNDER DIFFERENT FEATURE COMBINATIONS

RMSE	F1	F2	F3	F4	F5	F6	F7
simple-01	0.141	0.139	0.139	0.139	0.139	0.139	0.139
simple-02	0.125	0.122	0.121	0.123	0.123	0.121	0.122
simple-03	0.101	0.103	0.103	0.100	0.100	0.104	0.101
complex-01	0.191	0.215	0.215	0.192	0.193	0.204	0.213
complex-02	0.199	0.206	0.206	0.200	0.199	0.206	0.205
complex-03	0.189	0.198	0.195	0.189	0.189	0.196	0.194
RMS	0.162	0.170	0.169	0.162	0.162	0.167	0.168

is consistent with the conclusion drawn in Section IV-D. Considering both the positioning accuracy and computational complexity, fp_ratio is selected as the discriminative feature for the proposed CIR-based outlier rejection method.

2) *Comparison of CIR-UOINS and CHI-UOINS*: To visually compare the outlier rejection capabilities of the two methods in the complex scenario, the error distributions of retained UWB ranges for the complex-01 sequence are shown in Fig. 9. The upper part of each subfigure shows the raw range residuals and the residuals of ranges retained after outlier rejection by different methods. The raw UWB ranges are measured using the double-sided two-way ranging (DS-TWR) method, and the true ranges are derived from the ground-truth poses. In the lower part, the markers indicate whether UWB ranges are retained at each epoch. The markers are plotted only when the corresponding ranges are retained.

The results show that CHI-UOINS retains some ranges with significantly larger errors. Consequently, more markers are observed, indicating that range outliers are more likely to be missed in complex NLOS environments. This occurs because the chi-square test detects outliers based on range residuals and is sensitive to the accuracy of pose estimates. When NLOS effects become more severe, fewer ranges are available, and accurate absolute poses cannot be guaranteed. As a result, the rejection capability is reduced. In contrast, the CIR-based outlier rejection method identifies UWB outliers directly using the CIR data. Therefore, CIR-UOINS depends less on the number of available ranges, and range outliers can still be effectively detected in complex NLOS environments.

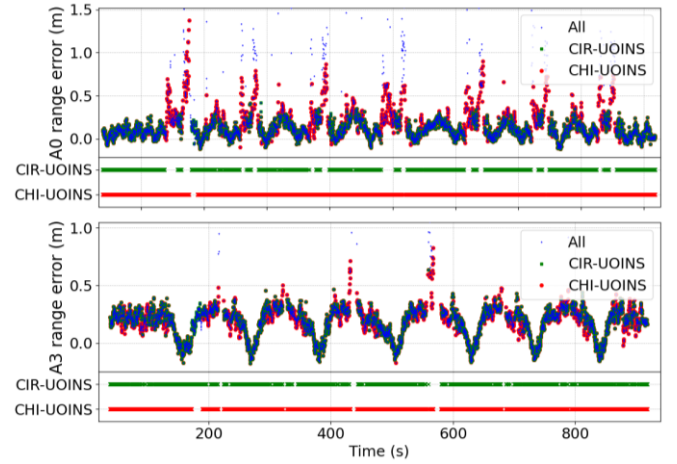


Fig. 9. Comparison of the outlier rejection performance on the complex-01 sequence. Here, “All” denotes the range errors between the raw ranges and the ground-truth ranges of UWB. The raw ranges are measured using the DS-TWR method, while the ground-truth ranges are derived from ground-truth poses. The A0 and A3 range errors represent the range errors from UWB base stations 0 and 3, respectively.

3) *Impact of ODO Measurements*: MODR-UOINS has been shown to rely on high-accuracy short-term relative poses provided by the ODO/INS odometry [15]. When ODO constraints are absent, the outlier rejection performance degrades significantly. However, ODO measurements are not always available in practical applications [34]. To analyze the dependence of the proposed CIR-based outlier rejection method on ODO measurements, the positioning errors of CIR-UOINS and CIR-UINS are compared, as shown in Table VI. Compared with CIR-UOINS, CIR-UINS shows only a slight increase in positioning errors. The result suggests that the proposed method can maintain stable positioning performance without ODO measurements. This is because the first-stage CIR-based likelihood ratio test uses the CIR data directly and does not require relative poses. Therefore, the proposed method is weakly dependent on ODO measurements and exhibits better adaptability than MODR-UOINS in scenarios with limited sensor information.

4) *Impact of Innovation-Based Chi-Square Test*: To further evaluate the effect of the innovation-based chi-square test, CIR-UOINS-NCHI is introduced by removing the chi-square test from CIR-UOINS. The positioning errors are shown in Table VI. Compared with CIR-UOINS, CIR-UOINS-NCHI exhibits large positioning errors in both simple and complex scenarios, indicating that some outliers remain after CIR-based outlier detection.

The measurements that pass the CIR-based likelihood ratio test but are subsequently rejected by the innovation-based chi-square test are further analyzed. These measurements account for only 0.66 % of the measurements accepted by the CIR-based likelihood ratio test, but their mean absolute ranging error, RMSE, and maximum ranging error reach 8.85, 9.54, and 37.67 m, respectively. Despite their small proportion, these measurements contain large ranging errors and degrade the positioning performance. Therefore, the innovation-based

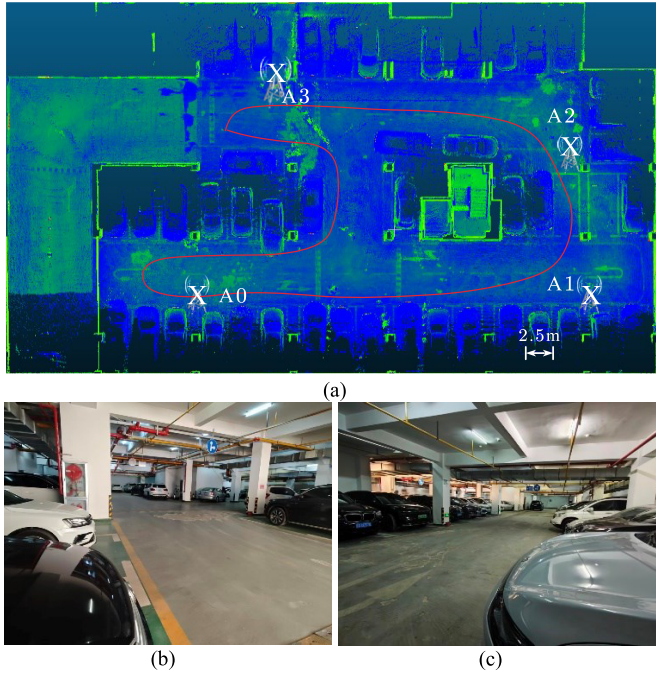


Fig. 10. Underground garage experimental environment. (a) Point cloud map of the underground garage. (b) Left view. (c) Right view.

chi-square test further rejects these remaining outliers and improves the positioning performance.

5) *Impact of Different Experimental Environments*: To further evaluate the effectiveness of the proposed method under different environmental conditions, additional experiments were conducted in an underground garage environment. The experimental environment is shown in Fig. 10, including the point cloud map in Fig. 10(a) and the left and right views in Fig. 10(b) and (c). The underground garage covers an area of approximately 1400 m² and contains concrete walls, pillars, and parked vehicles, which result in complex reflection and obstruction during UWB signal propagation. As shown in Fig. 10(a), four UWB base stations are deployed at different locations in the garage. Three test sequences, denoted as garage-01, garage-02, and garage-03, are collected along the marked red paths for evaluation, with each sequence lasting approximately 15 min. The ground-truth trajectories are obtained using the method described in [35], with an accuracy of approximately 2 cm.

The positioning errors of CIR-UOINS, MODR-UOINS, and CHI-UOINS are summarized in Table X. The same LOS/NLOS PDFs obtained from the semi-indoor rooftop experiments are directly used without additional data collection or parameter adjustment. The proposed CIR-UOINS achieves positioning performance comparable to MODR-UOINS and outperforms CHI-UOINS across all test trajectories. This demonstrates that the proposed CIR-based outlier rejection method can effectively reject range outliers in the underground garage scenario. Combined with the previous semi-indoor rooftop experiments, these results further verify the effectiveness of the proposed method under different complex environments.

TABLE X
POSITIONING ERRORS IN THE UNDERGROUND GARAGE ENVIRONMENT

Error (m)	MODR-UOINS		CHI-UOINS		Proposed CIR-UOINS	
	RMSE	CEP95	RMSE	CEP95	RMSE	CEP95
garage-01	0.18	0.31	0.63	1.22	0.17	0.28
garage-02	0.13	0.27	0.37	0.78	0.15	0.32
garage-03	0.16	0.30	0.60	1.15	0.17	0.30
RMS	0.16	0.29	0.55	1.07	0.16	0.30

VII. CONCLUSION

This article proposes a CIR-based UWB outlier rejection method to mitigate the effects of NLOS ranges in complex environments. The proposed outlier rejection method is integrated into a tightly coupled UWB-ODO-inertial navigation system as an application instance. Multiple CIR feature parameters are extracted from the CIR data, and range outliers are detected using a likelihood ratio test. As a result, the dependence on accurate pose estimation and the number of available measurements is reduced. Experimental results show that the proposed CIR-UOINS achieves a positioning accuracy of about 0.19 m in complex NLOS environments. The accuracy is comparable to that of the RANSAC-based method and shows an improvement over that of the chi-square test method. Overall, the proposed method achieves a good balance among the positioning accuracy, computational efficiency, and robustness. Future work will investigate the integration of additional sensors to further enhance the robustness of the system.

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