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Review

Survey on NLOS Identification and Error Mitigation for UWB Indoor Positioning

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Abstract: Ultra-wideband (UWB) positioning systems often operate in a non-line-of-sight (NLOS) environment. NLOS propagation has become the main source of ultra-wideband indoor positioning errors. As such, how to identify and correct NLOS errors has become a key problem that must be solved in high-accuracy indoor positioning technology. This paper firstly describes the influence of the NLOS propagation path on localization accuracy and the generation method of ultra-wideband signals, and secondly classifies and analyzes the currently available algorithms for ultra-wideband non-line-of-sight (NLOS) identification and error suppression. For the identification of NLOS, the residual analysis judgement method, statistical feature class identification method, machine learning method and geometric feature judgement method are discussed. For the suppression of NLOS propagation errors, weighting-based methods, filtering-based methods, line-of-sight reconstruction algorithms, neural network algorithms, optimization methods with constraints, and path tracing methods are discussed. Finally, we conclude the paper and point out the problems that need to be solved in NLOS indoor positioning.

Keywords: NLOS identification; error mitigation; UWB; indoor positioning

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1. Introduction

Location-based services have penetrated deeply into people's lives and become an important part of national defense, economic construction and social life. As the core technology of Internet of everything and location service applications, positioning technology has become more and more indispensable. With the development of mobile communication and positioning technology, the demand for precise positioning in indoor environments is gradually increasing. The global positioning system, the BeiDou Navigation system [1] and other mature positioning systems have been widely used in outdoor environments. However, in indoor environments, satellite positioning technologies cannot provide reliable positioning services due to the weakening and reflection of satellite signals, and so indoor positioning methods have been developed which are suited to the special characteristics of indoor environments. Traditional indoor positioning techniques include infrared positioning, Wi-Fi, Bluetooth, RFID [2,3], etc. It is obvious that the traditional positioning method is susceptible to RF signal interference and that the positioning accuracy can no longer meet the demands for an indoor positioning system. Therefore, researchers have started to search for indoor positioning technologies that can provide high accuracy and a low error level.

Ultra-wideband positioning technology [4] is a communication method that uses non-sinusoidal narrow pulses to transmit data. UWB technology can effectively discriminate between and reject multipath interference signals, the positioning error of UWB technology can reach several centimeter levels, and it is widely used in emergency rescue, intelligent logistics, intelligent prisons and other fields [5]. The current UWB wireless ranging algorithms are used to determine the location of the target nodes by calculating some parameters in the radio signals emitted from the target node to the reference base station as commonly used ranging methods, such as AOA [6], TOA [7], TDOA [8] and RSSI [9], are not universally applicable to UWB ranging considering the cost and difficulty of implementation in specific environments. On the other hand, the accuracy of UWB positioning techniques is affected by several factors, including non-visual propagation, but mainly including multipath effects, the number of reference base stations and non-line-of-sight propagation [10]. All these factors can lead to errors in the information measured by the signal, which can cause the degradation of positioning accuracy. The NLOS propagation is the main reason for the degradation of ranging accuracy [11]; therefore, the identification of LOS/NLOS propagation paths and the elimination of NLOS errors have become the key problems that must be solved for the development of high-precision indoor positioning technology.

2. Impact of UWB Propagation Path

The UWB propagation path is divided into two types: LOS propagation path [12] and NLOS propagation path, as shown in Figure 1. NLOS propagation [13] means that the signal is obscured by obstacles during propagation and cannot in essence propagate along a straight line.

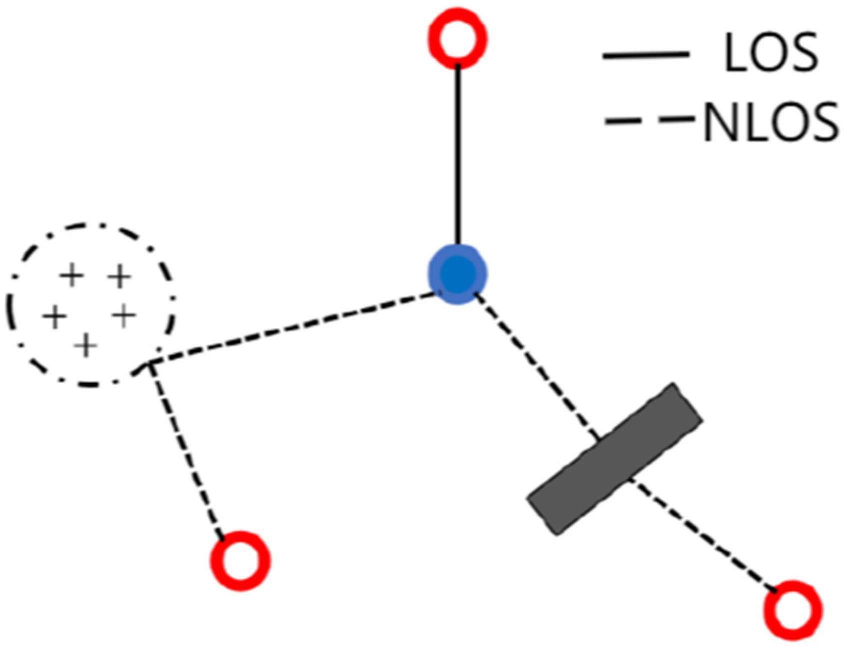

Figure 1. UWB propagation path classification.

The impact of the NLOS path on positioning accuracy mainly includes the following aspects:

Position Error: Due to the existence of different obstacles such as walls, wooden doors and glass doors in the room, the propagation speed and propagation time of the signal will change differently. In the LOS propagation environment, the true distance is affected by the standard error n_i, which is modeled by TDOA ranging as follows:

$$r_{i,1} = L_{i,1} + n_i \quad (1)$$

In the NLOS environment, the true distance is affected by the standard error n_i and the non-visual error e_i in the TDOA range measurement as follows:

$$r_{i,1} = L_{i,1} + n_i + e_i \quad (2)$$

The value of e_i is the measured signal propagation time that generates a positive time delay. Generally, the value of e_i is much larger than the measurement error, which makes the measured distance in NLOS environment larger than the actual distance, and in consequence the accuracy of node position estimation is adversely affected.

Positioning uncertainty: Due to the existence of NLOS paths, the model assumptions in the ultra-wideband positioning system cannot fully meet the actual requirements, which makes it difficult to accurately predict and control positioning errors; thus, the positioning uncertainty increases.

Therefore, it is important to identify and suppress the NLOS before positioning in order to achieve better positioning accuracy.

3. Ultra-Wideband Signal Generation Method

On the premise of conducting the exploration of the NLOS error identification and suppression algorithm, we must explore the generation method of the ultra-wideband signal [14]. This is because the frequency characteristics and power characteristics of the ultra-wideband signal will differ depending on the generation method of the ultra-wideband signal, which will affect the identification of the NLOS path and the effect of the suppression algorithm. The principles and characteristics of the generation methods of ultra-wideband signals are described in Table 1.

Table 1. Principles and characteristics of ultra-wideband signal generation methods.

Methods	Principles	Advantages	Disadvantages	Application Scenarios
Pulse Form	Repeat a short pulse signal several times by adjusting the pulse repetition rate, amplitude, width and other parameters	Short pulse width and long repetition period	Low signal energy, need for power amplification	radar, ranging, communications
Orthogonal Frequency Division Multiplexing	A technique for splitting data signals into pairs of subcarriers and transmitting them simultaneously	High data transmission, high spectrum utilization, strong resistance to multipath interference	High technical requirements for time synchronization, channel estimation	mobile communications, indoor positioning
Spread Spectrum Technology	Multiply the original signal with the pseudo-random code sequence to increase the signal bandwidth	Strong anti-interference ability and high security	High system complexity	satellite communications, indoor positioning

4. NLOS Identification Algorithm

Non-line-of-sight signal identification algorithms are used to determine whether NLOS propagation exists between the positioning base station node and the tag node to be located. In recent years, many scholars have classified indoor positioning scenarios where NLOS propagation exists into four categories, as shown in Figure 2.

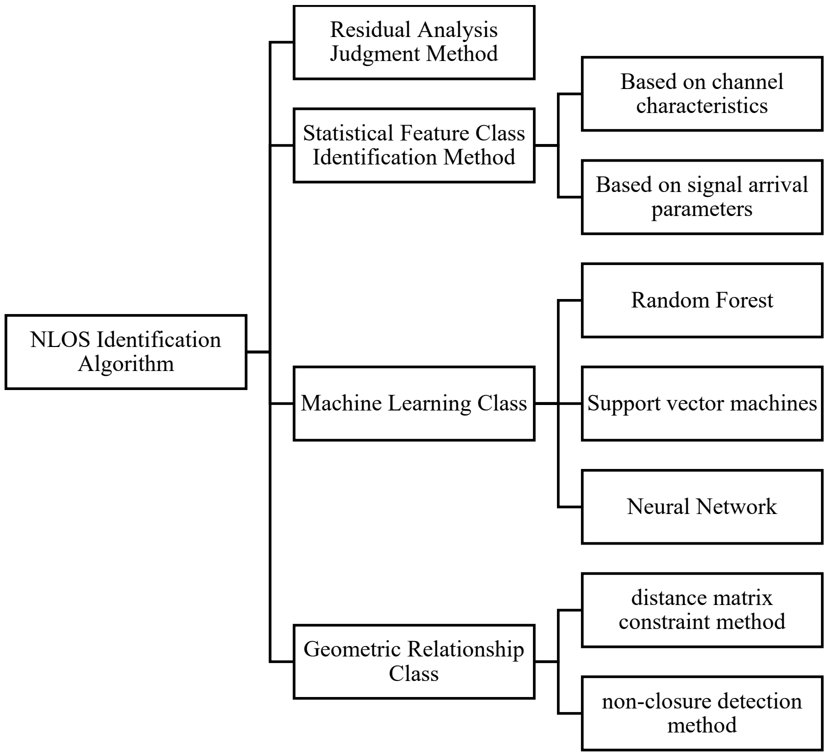

Figure 2. NLOS recognition algorithm.

5. Residual Analysis Judgment Method

The residual test method, by comparing the residuals between the model predictions and the actual observations, is used to make a judgment. Specifically, the residuals between the observed and model predicted values show significant deviations when the signal passes through a non-direct path. The NLOS error identification algorithm based on residual class, on the other hand, does not need to anticipate a priori information and directly estimates the intermediate position of the target to be measured to assist in the identification of the LOS/NLOS propagation path. In [15], a residual hypothesis testing algorithm for hyperbolic localization in a hybrid LOS/NLOS environment is proposed. When there are at least four LOS anchor nodes in a two-dimensional scene, it is possible to distinguish between LOS and NLOS in the absence of NLOS a priori information; ref. [16] uses a correction of the identified NLOS measurements by variance inflation. However, since the normalized innovation test uses empirical thresholds, NLOS may be detected incorrectly, and the equivalent variance may not be accurate enough. The detection algorithm of location residual (PRT), proposed in [17], is identified by applying approximate maximum likelihood algorithm to the number of LOS base station groupings before locating them. Additionally, the condition for dividing the LOS/NLOS base stations is whether the normalized residuals of the locations obey a χ^2 distribution with a degree of freedom of 1. The steps of the residual method test are as follows: in the first step, data are collected, such as TOA data; in the second step, the base stations are combined and the estimated values of the calculated positions are determined separately. For example, 3 to n base stations are selected from all base stations for combination and the AML algorithm is used for each combination to calculate the intermediate estimated position of the mobile station, there are

$$\sum_{i \cdot 3}^{n} C_n^i = m \tag{3}$$

intermediate estimated position results. Let the estimate of the kth combination be $\hat{\theta}(k) = [\hat{x}(k), \hat{y}(k)]^T$, $k = 1, 2 \ldots m$, where $\theta(1)$ is the estimate of C_n^n; in the third step, the fitted model is built and the normalized distance residuals are defined as:

$$\lambda_i^2 = \frac{(R_i - r_i(k))^2}{\sigma^2}, K = 1, 2 \ldots, m, i = 1, \ldots M \tag{4}$$

and

$$r_i(k) = \sqrt{(x(k) - x_i)^2 + (y(k) - y_i)^2} \tag{5}$$

where R_i denotes the measurement distance, σ^2 is the variance of the measurement error, and M is the number of all base stations in the combination. Then, the NLOS identification method is whether $\chi_i^2(k) \sim \chi^2(1)$.

The advantages of the algorithm are that it does not require complex mathematical calculations and it is simple to implement; it does not depend on the specific characteristics of the signal and is effectively adapted to different indoor environments; the algorithm is fast to implement and can be used to determine whether there is an NLOS error in real time. However, the algorithm still has certain drawbacks; firstly, the algorithm is only applicable to the case where the number of LOS base stations is not less than 3. For this case, there are certain number of solutions. For example, ref. [18] proposes to use the parameter values of AOA and TOA obtained from the measurement, to calculate the position of the mobile station by AML algorithm, and then to make the reverse extension of the measurement angle intersect with the chord of two circles at two points, and finally to compare the distance of the three points and the residuals of the three points with the set threshold value to determine whether the station is a complete LOS base station. There is also a reduction in the number of AML calculations caused by introducing the sum of squared distance residuals and NLOS recognition by using statistical features when there are less than three LOS base stations, thus improving the recognition rate. Secondly, the threshold selection of the algorithm has a large impact on the recognition accuracy, after which the optimal threshold can be selected automatically by methods such as machine learning. Finally, the residual test method can only be used to evaluate the fitting degree of the model and cannot directly determine whether the signal has passed through the non-direct path. Thus, it needs to be combined with the actual situation and other methods for comprehensive analysis.

6. Statistical Feature Class Identification Method

The statistical feature class identification algorithm is a kind of wireless signal transmission feature identification method based on statistical principles and models, and these features can reflect the signal in the transmission process of the multipath effect, attenuation, reflection, scattering and other physical phenomena. By analyzing these statistical features, we can determine whether the signal transmission path passes through obstacles to achieve LOS/NLOS identification. The more commonly used methods are the channel feature identification method and the signal arrival parameter identification method.

When the model and characteristics of a specific channel are known, the method based on channel statistics [19] mainly uses the statistical information of the received multipath components for LOS and NLOS identification, which include channel parameters such as mean, standard deviation, root-mean-square delay expansion, skewness, kurtosis, etc. The basic channel feature definitions and recognition principles are described in Table 2. To improve the NLOS recognition rate, researchers have implemented NLOS recognition by using multiple combinations of feature parameters. The main work in this category has been performed by [20–25].

Table 2. Channel basic features definition and identification principle.

Channel Characteristics	Definition	Identification Principle
Cliffe	Reflects the kurtosis of the sample data, which can be used to capture the amplitude statistics of the signal	NLOS channel cliff index is smaller than LOS.
Signal Energy	Amount of energy transmitted by the signal	LOS propagates signal energy higher than NLOS signal.
Maximum value	Maximum value of signal amplitude	The maximum amplitude of the signal propagated by LOS is larger than that of the signal propagated by NLOS.
Average additional delay	Delay characteristics of signals	The MED of LOS signal is larger than that of NLOS when the signal penetrates the obstacle and the propagation speed is reduced.
Root-mean-square time delay extension	Method for comparing similarity between two time series	The root-mean-square delay scaling of the NLOS channel will be greater.

In NLOS identification, the most widely used method is based on channel statistics. Based on the signal arrival parameters method used to determine whether the signal has passed through the NLOS path by analyzing the received signal's time delay, power, phase and other parameters, Fan et al. [26] identified the transmission status of the signal based on the Anderson–Darling test. The target node receives n different range values from the anchor node, and the set of measurements is

$$\mu_i = \frac{\sum_{j=1}^{n} d_i^j}{n}, \sigma_i^2 = \frac{\sum_{j=1}^{n}\left(d_i^j - \mu_i\right)}{n} \tag{6}$$

The AD statistics is defined as:

$$AD = -\frac{1}{n}\sum_{j=1}^{n}(2j-1)\left[lnz_j + ln\left(1 - z_{n+1-j}\right)\right] - n \tag{7}$$

where $Z_j = \varphi\left(\frac{d_i^j - \mu_i}{\sigma_i^2}\right)$, $\varphi(d_i)$ is the normal distribution function. The empirical value of multiple measurements at the threshold is:

$$CV = \frac{0.752n^2}{n^2 + 0.75n + 2.25} \tag{8}$$

If AD < CV, the measurement is considered to have been made under LOS conditions. Otherwise, the measurement is made under NLOS conditions. The advantage of this algorithm is that it does not require complex modeling or the simulation of the signal propagation environment and that it has a high practicality for signal processing in practical use. However, it is affected by the signal transmission distance and signal transmission power. In the case of line-of-sight propagation, however, the measurement error generally obeys a Gaussian distribution with zero mean and known variance. However, in the case of non-line-of-sight propagation, the measured values also have the interference of non-line-of-sight errors. It is then possible to determine the distribution of the measurement error in a comprehensive manner. The errors can be divided into two cases: namely, whether the LOS/NLOS propagation prior probability is known or not, and if the LOS/NLOS propagation prior probability is known. Indeed, ref. [27] uses a generalized likelihood ratio test to identify the LOS/NLOS propagation path. The generalized likelihood ratio detection can be expressed as:

$$\gamma(r) = \frac{maxP_d(r|H_1) > P(H_0)}{maxP_d(r|H_0) < P(H_1)} \tag{9}$$

Under the condition of H_1, the numerator of the above equation is taken as the maximum value, i.e., using the maximum likelihood method we can obtain $d = \frac{1}{N}\sum_{i=1}^{N} r_i - \mu_{nlos}$. Similarly, when the denominator is taken as the maximum value, $d = \frac{1}{N}\sum_{i=1}^{N} r_i$; thus, we obtain the discriminant formula of NLOS signal:

$$\frac{\sigma_{nlos}^2}{2\sigma^2(\sigma^2+\sigma_{nlos}{}^2)}\sum_{i=1}^{N}(r_i-r)^2 \overset{\geq}{<} ln\frac{P(H_0)}{P(H_1)} + \frac{N}{2}ln\frac{\sigma^2+\sigma_{nlos}^2}{\sigma^2} \tag{10}$$

Although the generalized likelihood ratio test algorithm is relatively simple to implement and can be adapted to a variety of signal models and statistical distributions, it is difficult to adjust and optimize it for uncertain or unknown signal distributions that can produce false positives and false alarms or which missed alarms in some specific cases. If the prior probability of LOS/NLOS propagation is unknown, NLOS propagation can be identified by testing whether the measurements obey a Gaussian distribution [28–30]. In recent years, tests such as K-S, A-D, chi-Square, gross test, skewness and cliffness tests have emerged [31–33]. The threshold value can also be obtained based on its false alarm probability $p(H_1|H_0)$ in order to identify the LOS/NLOS propagation path. As in [34], a statistical model based on the Neyman–Pearson criterion is proposed to determine a threshold value for identifying NLOS nodes by the non-visible error of AOA and NLOS. To reach this threshold value, the probability of false alarm is assumed to be fixed as:

$$\int_{x}^{\infty} P(x|H_0)dx = \gamma \tag{11}$$

Thus, the NLOS propagation signal is detected. $P\ (H_0)$ and $P\ (H_1)$ denote the prior probabilities of LOS and NLOS propagation, respectively, and when the values of $P\ (H_0)$ and $P\ (H_1)$ are unknown, the conditions for determining that NLOS holds are:

$$\frac{p(x|H_1)}{p(x|H_0)} > \gamma \tag{12}$$

The Neyman–Pearson criterion algorithm has a higher detection probability when the NLOS error is larger, and in the actual environment NLOS error is larger. Therefore, the algorithm has a good real-time performance. However, the N-P criterion only considers the power factor. This means that the false positive rate is higher in some cases, is affected by the signal strength, and cannot accurately determine the presence of the NLOS path when the signal is weak.

Further, the method based on statistical class features can model and analyze the overall statistical characteristics of the received signal, which has good adaptability for complex environments. However, the selection and analysis of signal features is the key factor, otherwise there will be misjudgment. On the other hand, the method is sensitive to the influence of signal noise, the multipath effect and other factors, and how to make appropriate corrections and adjustments should be the direction of future research. Finally, such algorithms are simple to implement and light in computation. However, they all require researchers to anticipate certain a priori information and so the applications of such methods are limited. In addition to some traditional statistics, more features should be introduced so as to fully reflect the characteristics of the signal.

7. Machine Learning Class

Theories based on machine learning and artificial intelligence have been successfully applied and developed in many disciplines, and many scholars have conducted a great deal of research in localization and NLOS recognition, which is a classification problem from the perspective of LOS/NLOS recognition. The most commonly used learning algorithms for classification problems include SVM (support vector machine), SGD (stochastic gradient descent algorithm), Bayes (Bayesian estimation), ensemble, KNN, etc.

The random forest algorithm [35] is an algorithm that integrates decision classification trees for prediction and classification. The specific steps are as follows: (1) acquire ultra-wideband data in different environments and label the category labels based on the real distance information; (2) reconstruct the features based on the measured ultra-wideband signal features; (3) randomly select the dichotomous recursive decision tree based on the reconstructed features; (4) select the samples from the training set described in step (1) to build a CART decision tree model; (5) draw M sets of data from the training set as training samples with put-back, use the CART decision tree model built in step (4) to make classification judgments, and repeat this process N times, N $\geq$ 30, so as to form a random forest model. Reference [36] utilizes several static and time-varying features of the channel impulse response (CIR), and the random forest algorithm adopted performs better than any other solution in terms of the solution trained with the extracted features.

Support vector machine [37] is a machine learning algorithm based on maximum interval classification, and its core idea involves mapping data onto a high-dimensional space for classification. In [38], a method using support vector machines as LOS and NLOS classifiers with a specific subset of features as training features was proposed. Reference [39] proposed the use of support vector machine (SVM) clustering to improve the localization performance. The specific steps are as follows: (1) multiple (more than 3) anchor nodes are arranged in the indoor localization area, any 3 anchor nodes are not in the same plane, and $N_c = C_N^3$ forms a combination of anchor nodes, where C_N^3 denotes the total number of combinations of 3 base stations selected from the total number of N anchors. (2) For each S_k (S_k represents the kth combination of anchor nodes), in the data collection phase, the data are tagged into two categories: 1 for when all anchor nodes are in LOS; -1 for when at least one anchor node is in NLOS. Additionally, the corresponding classifier should be trained, where G_k, $K = 1, 2 \ldots\ N_c$, and a total of N_c classifiers should be trained to form a complete classifier network. (3) In the test, the TOA measurement distance of each mobile station is combined as the input of the corresponding Nc classifiers, and the combination with output "1" is represented as the LOS base station combination. The combinations with "1" are de-duplicated and the unique value is taken to correctly identify the NLOS base stations. In recent years, the literature [40–42] has improved NLOS recognition rates by operations such as the optimization of the parameters of support vector machines and the dimensionality reduction of the input data.

The basic principle of neural network [43] classification is that it computes the input data according to certain rules and maps them onto a specific output class. The specific steps are as follows: (1) initialize the weights of all neuron nodes in the neural network; (2) feed inputs to the input layer receives and generate the outputs through forward propagation; (3) calculate the deviations based on the predicted values of the outputs, combined with the actual values; (4) give the output layer the deviations to allow all neurons to update the weights through the back-propagation mechanism; (5) hold together the complete process, from the second to the fourth step, of training the model and repeat the process until the deviation value is minimized, thus forming a neural network model. Convolutional neural network [44] methods recognize NLOS signals, the basic steps of which are: convolutional layer extracts initial features; pooling layer extracts main features; fully connected layer aggregates features and performs classification prediction. Cui et al. [45] proposed a method for use in identifying identify NLOS signals using a capsule network. The proposed capsule network model includes a convolutional layer, main capsule layer and channel capsule layer. This capsule network will mainly separate different classes of channels by applying two types of channel capsules, LOS capsule and NLOS capsule. AdaBoost is a strong learner algorithm, which can improve prediction accuracy. A new direction is proposed for LOS/NLOS recognition. The algorithm first trains a number of weak learners on the sample data, and then adjusts the weights of the previously misidentified samples to train a weak learner until the weak learner reaches the specified required index. Thus, the LOS/NLOS recognition rate can be improved.

As shown in Table 3, the basic idea of recognition based on machine learning algorithms is to learn the significant differences between NLOS/LOS by training models on a large amount of sample data and building classification models that can be used to classify new data. This type of algorithm can handle complex nonlinear relationships, is suitable for multi-dimensional feature data, and has high recognition accuracy. However, there are still some drawbacks. Firstly, it is easy to over-fit for small amounts of data; secondly, this algorithm requires operations such as data enhancement and regularization; and finally, the results and parameter selection for the classifier require several experiments, which are more time-consuming and computationally resource-intensive than traditional methods. The future improvement direction of such algorithms is the aim to design new feature extraction methods and classifier results for the problems in special scenarios.

Table 3. Comparison of the advantages and disadvantages of machine learning algorithms to identify NLOS.

Methods	Advantages	Disadvantages
Random Forest	Highly scalable and efficient; interpretable	For highly correlated features, performance is affected
Support vector machines	High accuracy, good generalization to small samples, able to handle high-dimensional data	Sensitive to data noise and missing values, need to manually select the appropriate kernel function, have problems in handling large data sets
Neural Network	Capable of automatically extract features with high accuracy	More complex network structure, poor model interpretability

8. Geometric Relationship Class

The geometric relationship method is a geometry-based method that can determine whether the transmission path of a signal is blocked by geometric measurement features such as the distance and angle between nodes for NLOS/LOS judgments. It is specifically divided into the distance matrix constraint method and the non-closure detection method.

The principle of the distance matrix constraint method is to model the distance matrix when the wireless signal propagates in space. Additionally, when the signal is transmitted, according to the geometric relationship, all distance values are fixed in the LOS case, while in the NLOS case, some distance values change, so to distinguish LOS and NLOS. Reference [46] grouped all anchor nodes, combined with the Cayley–Menger determinant, to detect the presence of NLOS signals in each group, and then determined the LOS and NLOS anchor points based on the detection results. The algorithm has high signal path classification accuracy and scalability. However, the distance matrix constraint method requires accurate location information, high network requirements, and requires a certain computational complexity to implement, which requires the implementation of efficient algorithms and data structures.

The basic principle of the non-containment measurement method is to use the time delay and amplitude information of the received signal, combined with the location information of the anchor node and the sparsity assumption, to determine whether there is multipath propagation. In [47], a non-closure checking algorithm that can be applied in NLOS environments with sparse anchor nodes is proposed. The specific steps are as follows:

1. Determine the estimated position value based on the TOA measurements.
2. Decompose the TOA measurements using the approximate estimated position to form the statistics for non-closure detection.
3. Perform the non-closed detection.
4. If it passes, proceed to the next detection step; if it fails, put the starting and ending points into the spoofed NLOS set.
5. Find the NLOS node from the spoofed NLOS set.

The algorithm achieves good NLOS identification without a large number of redundant measurements. However, the non-closure detection method requires certain computational resources and other besides factors affect the performance of the algorithm.

The advantages of geometric relationship-based class algorithms are wide applicability, high accuracy and simplicity. However, there are also certain disadvantages, such as the dependence of geometric relationship, the sensitivity to signal strength and the restricted environment, each of which need to be considered and overcome in practical application.

9. NLOS Error Suppression Algorithm

Most of the methods used to suppress NLOS propagation or correct NLOS errors are based on NLOS identification and some algorithms to mitigate the impact of NLOS propagation on localization accuracy. Many studies have also proposed algorithms that are feasible for use in specific scenarios to suppress NLOS errors, as shown in Figure 3.

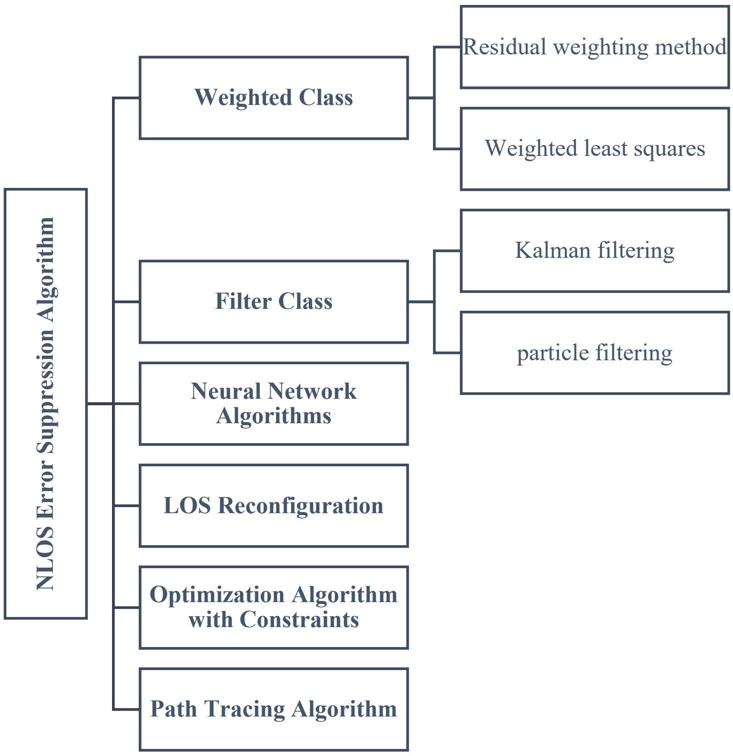

Figure 3. Classification of NLOS error suppression algorithms.

10. Weighted Class

The basic idea of the weighted localization method is to use all available measurements for localization estimation and to set a weighting factor to the TODA/TOA residuals according to the characteristics of the measurements. In the LOS case, the measured TODA/TOA values are assigned larger weights. Conversely, in the NLOS case, the measured values are assigned smaller weights to effectively reduce the impact of NLOS errors on positioning accuracy. Commonly used algorithms include the residual weighting method and the weighted least squares method.

Reference [48] proposed a residual weighting (RWGH) algorithm, and the basic steps of the RWGH algorithm are as follows.

(1) Give M ($M > 3$) distance measurements in the form of $N = \sum_{i=3}^{n} \binom{M}{i}$ distance measurement combinations.

(2) Each combination consists of a BS index set $\{S_k \mid k = 1, 2, N\}$ for each combination, and so calculate the intermediate LS estimates of x and Res.

$$x_k = \arg\min_{x} Res(x; S_k), R_{es}(x_k, S_k) = \frac{R_{es}(x_k, S_k)}{size\ of\ S_k} \quad (13)$$

(3) Determine the final estimate of x as a weighted linear combination of the intermediate estimates from step 2. The weights are inversely proportional to the estimated Res.

$$x = \frac{\sum_{k=1}^{N} x_k (R_{es}(x_k, S_k))^{-1}}{\sum_{k=1}^{N} (R_{es}(x_k, S_k))^{-1}} \quad (14)$$

In recent years, researchers have optimized the residual weighting algorithm in order to reduce the complexity of the residual weighting algorithm and improve its localization accuracy. For example, in [49,50], the complexity of the residual weighting algorithm was reduced by selecting the smallest combination of normalized residuals in different ways and then performing weighted summation; in [51,52], for the TOA/AOA hybrid localization method, the localization accuracy was improved by selecting a suitable iterative minimum residual criterion and using the estimated result of selecting the iterative minimum residual combination as the final MS position, and the algorithm can play an obvious role in NLOS error suppression under certain conditions. The algorithm can provide significant suppression of NLOS error suppression under certain conditions. The advantage of this algorithm is that only one measurement needs to be made, and the variance of the measurement noise as well as the mean and variance of the NLOS error do not need to be known. The disadvantage is that it requires the participation of multiple anchor nodes and high computational complexity.

Least squares are a mathematical optimization technique [53] that finds the best functional match of data by minimizing the quadratic sum of errors, and is usually used to find unknown data and minimize the quadratic sum of errors between the found data and the data. The characteristic equation of the least squares' formula is as follows.

$$AX = b \quad (15)$$

where A is an $n \times k$ matrix; X is a $k \times 1$ column vector; b is an $n \times 1$ column vector. If the number of equations is greater than the number of unknowns, the system of equations has no solution. However, a solution can be found using the least-squares method, meaning that this solution minimizes the quadratic sum of errors for the system of equations. It is worthy of note that the quadratic sum of solutions to the equations is

$$E^2 = \sum_{i=1}^{n} \left[\sum_{j=1}^{k} a_{i,j} x_j - b_i \right]^2 \quad (16)$$

If $\left(A^T A\right)$ is a non-singular matrix, then the least-squares solution of the equation is given as follows,

$$X = \left(A^T A\right)^{-1} A^T A \quad (17)$$

In [54,55], based on the assumption of known knowledge of NLOS measurements, the least-squares algorithm was first used to perform global search, then the best initial value was obtained by threshold screening and weight calculation, and finally it was used as the input of Taylor's algorithm for iterative solution, and the localization accuracy was improved by 63% compared with the LS algorithm. In [56], for the case of a mixed LOS/NLOS environment with unknown anomaly variance case, a weighted least-squares method based on Hampel and skip-filter was proposed to solve the final estimated position, which suppressed the error significantly.

The algorithm has the disadvantage of requiring the participation of multiple anchor nodes and decreasing the performance of anchor nodes with the increase in anchor nodes, and the problem of setting the weighting factor must be considered if the NLOS error is to be suppressed. Reference [57] proposed a method for the dynamic determination of the weighting factor. As the possibility of being affected by NLOS error increases with the distance between the mobile station and the base station in the mobile communication channel, the weighting factor is determined and denoted as:

$$a_i = \frac{1}{d_i^{\varepsilon}} \tag{18}$$

where ε is the channel parameter taken as 0.5, d_i^{ε} is the estimated distance between the mobile node and the anchor node.

11. Filter Class

The basic principle of using a filtering algorithm to suppress the NLOS error is to remove the multipath interference caused by the NLOS path through filtering to improve the signal-to-noise ratio of the signal, thus reducing the error The commonly used filtering algorithms for this task are Kalman filtering and particle filtering.

The basic principle of Kalman filtering in the suppression NLOS errors is to use prior knowledge and observations to infer the state of the target in order to calculate an estimate of the current state. The Kalman filter algorithm is divided into two phases, prediction and update [58], and its state equation and measurement equation are formulated as follows.

$$X_n = AX_{n-1} + B\mu_{n-1} + W, Y_n = H_n X_n + v_n \tag{19}$$

where X_n, Y_n are the state and measurement values, respectively, A is the state transfer matrix; B is the gain of the optional control input μ, W denotes the process noise, which is disturbed by many external factors, v_n is the observation noise, which contains the error generated between measurement times, and H_n denotes the measurement matrix of the system. The traditional Kalman filtering algorithm described method in [59,60] calculates the sample standard deviation for TOA data measured over a period of time and considers the TOA data to contain NLOS errors when it is greater than a set judgment threshold. The shortcoming of this method is that the filtered output results are prone to jumping. To solve this problem, researchers have improved the parameter settings of the Kalman filtering algorithm. For example, ref. [61] identifies and suppress NLOS error with a Kalman filter based on the credible factor; ref. [62] suppresses the NLOS error based on the asymmetry of TOA probability density function, which is applicable no matter what distribution the NLOS error obeys or in the absence of NLOS error. However, the method is computationally intensive in the process of probability density estimation and the real-time performance of the algorithm. The algorithm has poor real-time performance. The advantage of this algorithm is that it can deal with unstable measurement and positioning data in real time, but the Kalman filter algorithm requires high accuracy of the system model and noise model and it cannot deal with nonlinear systems; additionally, if a linear system is to be used, the extended Kalman filter [63] or the traceless Kalman filter algorithm [64] is required.

In the real world, people are mostly faced with nonlinear and non-Gaussian systems. In order to better solve the nonlinear filtering problem, researchers have proposed the particle filtering algorithm [65]. The particle filtering algorithm approximates the distribution of the localization points by introducing a set of random particles, and resamples and updates them according to the observed data to finally obtain the posterior distribution of the localization points. In terms of suppressing NLOS errors, the basic principle of the particle filtering algorithm is to compensate for the effects of NLOS errors by dynamically adjusting the weights of the particles. The literature [66] takes the approach of filtering the data acquired by the UWB system in NLOS environment twice to reduce the effect of NLOS errors, thus achieving precise positioning. The advantages of this algorithm are that it can handle nonlinear and non-Gaussian system models, which require less assumptions for the model, and can increase the number of particles to reduce the NLOS error. However, there are also some disadvantages. Due to the large number of particles to be processed, the computational complexity is high. In addition, due to the introduction of randomness, the computational results of the particle filtering algorithm have some uncertainty, and several trials are needed to verify the reliability of the experiments.

12. Neural Network Algorithms

Neural networks are suitable for dealing with inaccurate and ambiguous information that requires many factors and conditions to be considered simultaneously. Therefore, the use of neural networks to estimate the parameter λ of the unknown NLOS error model can indirectly suppress the effect of NLOS errors and improve positioning accuracy. Reference [67] proposed a semi-supervised SVM learning method to mitigate UWB ranging errors in NLOS environments, which incorporates unlabeled measurements into the training data pool by self-training and assigns different weights to labeled and unlabeled measurements to reduce the accumulated errors. By optimizing deep neural networks, CNNs and long and short-term memory methods, the problem of adaptive NLOS suppression was investigated in [68]. In the proposed method, the alignment of the CIR in reprocessing was achieved by correlating all channel impulse responses (CIRs) with the associated first CIR and shifting the peak index of the associated CIR; then, the normalized and aligned CIRs were used as the input to the CNN model. In order to obtain the time series information and analyze the dependencies between elements from the CIR, the long- and short-term memories were further developed.

The advantage of this algorithm is its strong nonlinear fitting ability, which means it can be trained according to different NLOS error cases, thus allowing adaptation to various cases of NLOS errors. It has a certain generalization ability. However, there are also certain disadvantages, such as the need for a large amount of training data, which may lead to overfitting and underfitting phenomena when the data are insufficient; a large number of matrix calculations are required, so the computational complexity is high, requiring strong computing power and time cost; the neural network algorithm is a black box model, which struggles to explain the internal mechanism and decision-making process and may cause trouble in the application scenario.

13. LOS Reconfiguration

In the identified LOS/NLOS case, ref. [69] used the LOS reconstruction method to suppress the NLOS error and thus improve the localization accuracy. The steps of the LOS reconstruction method are as follows: firstly, the distance measurements are smoothed and the NLOS error is assumed to be a positive number. Then, the NLOS error is corrected by the pre-know pair σ_m. After the first step of LOS/NLOS identification process, the deviation of the measured value from the smoothed value $d_m(t_i) - S_m(t_i)$ can be calculated for each moment, and a t_n can be found after a long enough time so that the negative deviation of the measured value from the smoothed value is at a maximum value at the moment t_n. The smoothed curve shifts to the point at t_n and then shifts upward due to a_m. The curve after two shifts is the reconstructed curve. References [70,71] also used the empirical value of the average excess delay caused by NLOS in a real environment for LOS reconstruction. Although the algorithm is simple in principle and small in computation, the drawback is also obvious in that the method requires a large amount of data. In addition, due to the variance of the distance measurement in the LOS environment and when the NLOS error obeys the delta distribution, the reconstructed distance differs significantly from the true distance, meaning that the NLOS error cannot be effectively suppressed.

14. Optimization Algorithm with Constraints

Optimization methods [72] are based on the use of mathematical calculations and use the ideas and methods related to optimization to solve engineering problems as a way to find the best decisions for the problem at hand and construct the optimal solutions. References [73–76] directly suppresses the NLOS errors by the use of constrained optimization methods, including three-step optimization algorithms and linear quadratic programming algorithms. Then, the optimization problem with constraints is expressed in a generalized form as:

$$\begin{array}{ll} min & f(\boldsymbol{x}) \\ s.t. & g_j(\boldsymbol{x}) = 0, j = 1, \ldots, m, \\ & h_k(\boldsymbol{x}) \leq 0, k = 1, \ldots, p. \end{array} \tag{20}$$

When the objective and constraint equations are linear, the optimization problem is transformed into a linear program; conversely, if there is nonlinearity in the equations, the problem is transformed into a nonlinear program. Reference [77] proposes a new algorithm for suppressing NLOS, namely the RSA algorithm, which suppresses the effect of NLOS by multiplying the measured distance of each base station by a scale factor that takes values between 0 and 1. The main idea is to find the optimal solution for the nonlinear equations with constraints that exploit the geometric relationship between the estimated location of the mobile station, the cell geometry, and the positioning circle of the three base stations. Wang et al. [78] convert the localization problem into one of detection-assisted optimal planning, where all distance measurements are initially considered as NLOS links with unknown non-negative deviations and then the target node is estimated in an iterative manner location. In addition, the maximum likelihood estimates of the target node locations and NLOS deviations are relaxed to follow a semi-definite plan, and the geometric relationship of NLOS deviations is introduced as a constraint for optimization.

The advantages of this algorithm include high flexibility, wide applicability and scalability. However, there are some drawbacks. The optimization algorithm with constraints requires a large amount of computation and optimization, and therefore requires sufficient computational power and time. The performance of the algorithm is limited by the precision and accuracy of the model and the interference of noise.

15. Path Tracing Algorithm

Most of the commonly used NLOS error identification and suppression algorithms are based on NLOS propagation models and their probabilistic statistical properties, but they vary greatly in different environments [79]. Therefore, researchers have proposed the latest method for NLOS error identification and suppression, which is known as path tracing. It features a new approach to improve localization accuracy by "exploiting" the information of multiple arrival paths instead of adhering to the traditional idea of "suppressing" multipaths and non-direct paths. It uses path tracing to trace the actual propagation path of the signal to map the propagation path of the signal and then identify and utilize the NLOS path based on it. For example, ref. [80] used the ray tracing LOS/NLOS algorithm to predict the effect of NLOS propagation on signal quality in a complex 3D environment, thus determining the maximum capability of the localization system in terms of accuracy.

The path tracking algorithm [81] focuses on the direct, reflected, and edge-bound cases of the signal. If only direct and reflected signals occur during propagation, the resulting signal propagation path is called a pointing path; conversely, if the signal excessively bypasses during propagation, the resulting signal propagation path is called an area pointing path. The path tracking algorithm reduces the NLOS error by: building a multipath model, where the NLOS path is modeled as an additional path; using extrapolation, the analysis of obstacles to estimate the effect of the NLOS path, and then correcting the results of the algorithm; performing statistical analysis of multiple measurements to reduce the NLOS error; and using multiple receivers to receive signals and fusing the data from the receivers.

Although the algorithm is highly adaptable and suitable for real-time use, the tracking algorithm not only requires high computational resources and hardware support, but also requires multiple instances of sampling and modeling of the signal, resulting in high computational complexity and high demands being placed on the algorithm.

16. Conclusions

Starting from the fact that NLOS error is the main reason affecting the high accuracy of future ultra-wideband positioning, this paper analyzes the impact of NLOS error on positioning accuracy. Then, the existing NLOS error identification and suppression algorithms are classified and studied, and the current latest NLOS error suppression algorithm is discussed. The future research work can be carried out from the following aspects: (1) the current NLOS error suppression and recognition algorithms have some shortcomings such as the need for a priori information and high complexity of the algorithms, therefore, there should be a solution on how to integrate related techniques to improve the robustness of the algorithms; (2) for the existing NLOS recognition of indoor positioning algorithms, the future study should be more inclined to develop some statistical feature-based algorithms so that the application of NLOS sparse or dense scenarios can improve the recognition accuracy; (3) in view of the shortcomings of the current path tracking, other techniques can be combined to further improve the accuracy and real-time of the path tracking algorithm

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