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Single-base station hybrid positioning algorithm based on LOS identification

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Abstract

In the complex multipath propagation environment, whether there is a line of sight (LOS) path will directly affect the positioning accuracy. Therefore, this paper proposes a single base station hybrid positioning algorithm based on LOS identification. In the algorithm, we first construct multiple features based on channel state information with LOS and without LOS in statistical distribution and use these features and gradient boosting decision tree to determine whether there is a LOS path in the environment. Then for the environment with a LOS path, we proposed a positioning method based on the estimation of signal parameters via rotation invariant technology algorithm which can be used to jointly estimate the angle of arrival and time delay of the LOS path for positioning, while for the environment without LOS path, we propose a positioning method based on adaptive genetic algorithm. Finally, a single base station hybrid positioning algorithm based on LOS identification and the corresponding positioning methods. Simulation results show that the proposed hybrid positioning algorithm can achieve high-precision positioning in the complex multipath propagation environment.

Keywords: Single-base station, LOS identification, Hyprid positioning, ESPRIT, NLOS mitigation

1 Introduction

With the arrival of the *fifth generation mobile communications* (5 G) era, humanity will enter an era of interconnected everything. Traditional industries such as automobiles, health, manufacturing, and entertainment will also become more intelligent, automated, and internet-based due to 5 G. In these applications, in addition to the well-known 5 G technical indicators such as high speed, low latency, and high reliability, high-precision positioning is also a very important technical indicator.

Generally, the positioning technology can be mainly divided into two categories, range-based positioning and range-free positioning. The core of range-based positioning is to calculate signal measurements from one or more reference transmitters at the receiving end, and then use a certain positioning algorithm to obtain position estimation. Commonly used measurement values include *received signal strength* (RSS), *time of arrival* (TOA), *time difference of arrival* (TDOA), *time of flight* (ToF) or *angle of arrival* (AOA) [1–10], but the accuracy of range-based positioning is largely affected by the accuracy of parameter estimation, and the accuracy of parameter estimation is often affected by the *line of sight* (LOS) path of signal propagation, which limits its application in practical scenarios. The method that does not require distance usually uses position fingerprints constructed by signals, images, sensors, etc. to achieve fingerprint positioning. Compared to range-based methods, it is not affected by LOS path and can achieve ideal positioning performance in complex multipath environments. However, its positioning accuracy is somewhat different from range-based positioning algorithms with ideal parameter estimation. Therefore, the prerequisite for achieving high-precision positioning is how to carry out effective LOS path recognition and design more effective positioning algorithms based on the recognition results. That is to say, for the LOS environment and the *not LOS* (NLOS) environment, different positioning methods should be used according to different environments according to the LOS recognition results.

In the LOS environment, the signal travels in a straight line between the *base station* (BS) and the *mobile station* (MS). At this time, the direction and distance information between the BS and the MS can be obtained more accurately. Therefore, the positioning method based on ranging [5] has higher positioning accuracy and is more widely used. For the positioning method based on ranging, the premise of achieving high-precision positioning is to estimate the required positioning parameters. The most commonly used positioning parameters are AOA [6, 7] and TOA [8], and the traditional subspace methods, such as *multi-signal classification* (MUSIC) [11, 12] and *estimating signal parameters via rotational invariance techniques* (ESPRIT) algorithm [13] can been widely used to estimate these parameters. However, in the actual environment, due to the existence of obstacles such as buildings and trees, the signal will be reflected or refracted between the BS and the MS, which results in the NLOS environment and will cause a large deviation in the measurement of propagation time and propagation distance [14]. At this time, the range-based positioning method will have a larger positioning error. In the NLOS environment, an effective approach is to use the correspondence between propagation features and positions to establish a fingerprint database for localization. In this case, a direct approach is to utilize the existing channel propagation model knowledge to design a spatial fingerprint feature localization scheme. In this case, the key is how to recognize the LOS path.

The actual prorogation environment is not only complicated but also often unpredictable. Therefore, it is difficulty to recognize the LOS environment and the NLOS environment. For the LOS identification, a typical method is based on channel characteristics [15]. This type of method extracts from the *channel impulse response* (CIR) features that have significant differences in the statistical distribution of LOS and NLOS environments, such as the total signal energy, kurtosis, *root mean square delay spread* (RMS), etc., and then use these features for LOS/NLOS identification. Reference [16] uses the extracted signal features to perform LOS/NLOS identification using binary hypothesis testing. In recent years, with the rapid development of machine learning technology, many scholars have applied machine learning technology to the research of LOS/NLOS identification. Since the identification of LOS and NLOS can be regarded as a binary classification problem, some classic classification algorithms based on machine learning, such as *support vector machine* (SVM), have also been applied to LOS identification. Reference [17] uses kurtosis rise time, and other characteristics, and uses the *least square-SVM* (LS-SVM) algorithm to complete the identification and mitigation of NLOS in the *Ultra Wideband* (UWB) systems, and proposes several kinds of positioning schemes. Reference [18] also studies the identification and mitigation of NLOS in the UWB positioning system. The reference uses the *relevance vector machine* (RVM) algorithm to identify NLOS and mitigate the NLOS signal to improve the accuracy of TOA positioning. Reference [19] uses the *gradient boosting decision tree* (GBDT) to study LOS/NLOS identification in mmWave systems.

Once the signal propagation environment is identified, different positioning methods can be used for positioning according to different environments. For the LOS environments with a LOS path, simple and effective ranging-based methods are generally used. For the NLOS environment without a LOS path, it is necessary to reduce the positioning error caused by NLOS propagation. Therefore, many scholars have researched NLOS error mitigation technology [20–22]. Reference [23] proposes a semidefinite programming (SDP) method with new constraints and converted the TDOA positioning model to the TOA positioning model to effectively alleviate the NLOS error in the TDOA system. Reference [24] proposes an *equality-constrained Taylor series robust least squares* (ECTSRLS) technology, which suppresses the residual NLOS range error in the indoor positioning system by introducing robustness into the Taylor series least squares method. Reference [25] uses a *second-order cone relaxation weighted least square* (SOCR-WLS) method to reduce the impact of NLOS errors on TOF/TDOA-based positioning algorithms. The algorithm simplifies the constraint conditions of the weighted least squares formula through the second-order cone relaxation and does not require any statistical characteristics or parameters, but it has high computational complexity. However, the algorithms in the above references all have certain requirements on the number of BSs, generally no less than 3, when the number of base stations is small, the positioning accuracy will be greatly reduced. At present, for positioning in the NLOS environment, most of the existing research uses multiple BSs, and the research on the positioning of a single BS is still limited.

To overcome the above-mentioned challenges in the complex unknown positioning environment, we propose a single-BS hybrid positioning method based on LOS identification. The contribution of the proposed method is summarized as follows:

1. We study several machine learning methods for LOS identification. We evaluate the identification performance of GDBT and *Random Forest* (RF) based on the positioning data. When using different training functions and training strategies, these methods show different performances.
2. To solve the problem that most of the positioning methods in the NLOS environment use multiple BSs, we propose a single-BS positioning method that directly uses the NLOS path for positioning. The final position of the MS can be obtained by solving the optimization problem. The advantage of this method is that it can satisfy single BS positioning and can achieve relatively high positioning accuracy.
3. We propose a hybrid positioning method based on LOS identification, which can improve positioning accuracy in a complex and unknown positioning environment. We first use LOS recognition technology to judge the positioning environment. Then, according to the identification results, we use different positioning methods

in different positioning environments to complement each other's advantages and improve positioning accuracy. Simulation results prove that the proposed scheme can achieve high-precision positioning in the complex unknown positioning environment.

2 System model

Figure 1 shows the positioning system model. In the positioning system, there is a BS with a known location and a mobile MS with an unknown location, and a number of scatterers are randomly distributed between the BS and MS. Assume that the MS is equipped with a *uniform linear array* (ULA) composed of M_r antennas and the BS is equipped with a ULA composed of M_t antennas. The dotted line represents the LOS path, and the solid line represents the NLOS path. And we assume that the signal only experiences one reflection when it encounters a scatterer. Figure 1 also shows the position-related parameters in the channel. These parameters include θ_l, φ_l, τ_l and $d_l = c \cdot \tau_l$, which represent *angle of arrival* (AOA), *angle of departure* (AOD), time delay, and path length of the l-th path (c represents the speed of light), where the range of AOA and AOD are $[-180°, 180°)$.

For the positioning system with L paths, the CIR between the m_t-th transmitting antenna and the m_r-th receiving antenna can be expressed as

$$h_{m_t m_r}(t) = \sqrt{\rho} \sum_{l=1}^{L} \beta_l e^{\frac{j2\pi d(m_r-1)\sin\theta_l}{\lambda}} e^{\frac{j2\pi d(m_t-1)\sin\varphi_l}{\lambda}} s(t-\tau_l) \tag{1}$$

where ρ represents channel fading, β_l is the equivalent channel gain of the l-th path, λ is wavelength, $d = \lambda/2$ is antenna array spacing, $s(t)$ represents the pulse shaping filter.

Sampling (1) with T_s as the sampling interval, the corresponding discrete-time channel CIR can be expressed as

$$h_{m_t m_r}(t_n) = \sqrt{\rho} \sum_{l=1}^{L} \beta_l e^{\frac{j2\pi d(m_r-1)\sin\theta_l}{\lambda}} e^{\frac{j2\pi d(m_t-1)\sin\varphi_l}{\lambda}} s(t_n - \tau_l) \tag{2}$$

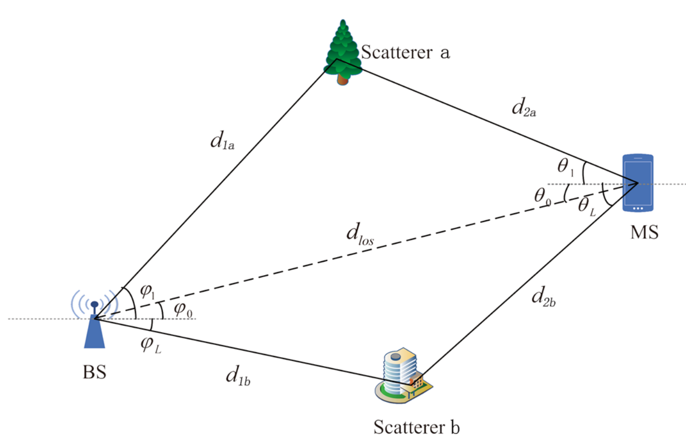

Fig. 1 System model with channel parameters

where $0 \le n \le N-1$, N is the number of sampling points, that is, the equivalent time domain channel length, $t_n = NT_s$.

3 LOS identification

Since the hybrid positioning method in this paper uses different positioning methods for the two different propagation environments of LOS and NLOS, it is necessary to identify the LOS/NLOS propagation environment first, that is, to determine whether there is a LOS path in the environment.

3.1 Feature selection

To identify LOS and NLOS, we must first extract from the CIR the characteristics of statistical distributions that have obvious differences under the conditions of LOS and NLOS. Therefore, the selection of features is very critical. First, use (2) to get the CIR under LOS and NLOS conditions to prepare for feature extraction.

Then, we select the following features to identify the LOS path:

1. Total energy of received signal

$$\varepsilon = \sum_{n=0}^{N-1} \left|h(t_n)\right|^2 \tag{3}$$

In the NLOS propagation environment, the signal will be reflected or refracted due to the existence of obstacles, so the signal attenuation is greater, making the energy and power of the received signal smaller. Therefore, the total energy of the received signal and the maximum received power are often used for LOS/NLOS identification. Since the two have a relatively strong correlation, it is enough to select one of them for identification. In this paper, the total energy of the received signal is selected as the identification feature.

2. Kurtosis, defined as the ratio between the fourth and second moments of the received signal amplitude, can be used to measure the peak value of the amplitude probability distribution.

$$\kappa = \frac{E\left[\left(\left|h(t_n)\right| - \mu_{|h|}\right)^4\right]}{E\left[\left(\left|h(t_n)\right| - \mu_{|h|}\right)^2\right]^2} = \frac{E\left[\left(\left|h(t_n)\right| - \mu_{|h|}\right)^4\right]}{\sigma_{|h|}^4} \tag{4}$$

where $E(\cdot)$ represents expectation, $\mu_{|h|}$ and $\sigma_{|h|}$ respectively represent the mean and standard deviation of $h(t_n)$, can be represented by (5) and (6) respectively

$$\mu_{|h|} = \frac{1}{N} \sum_{n=0}^{N-1} \left|h(t_n)\right| \tag{5}$$

$$\sigma_{|h|} = \sqrt{\frac{\sum_{n=0}^{N-1} \left(\left|h(t_n)\right| - \mu_{|h|}\right)^2}{N}} \tag{6}$$

Because the signal attenuation is greater in the NLOS propagation environment, the signal amplitude in the NLOS environment is usually smaller than the signal amplitude in the LOS environment, so the kurtosis value under the LOS condition is higher than the kurtosis value under the NLOS condition.

3. Skewness

$$s = \frac{E\left(\left|h(t_n)\right| - \mu_{|h|}\right)^3}{\sigma_{|h|}^3} \tag{7}$$

where $\mu_{|h|}$ and $\sigma_{|h|}$ can be represented by (5) and (6) respectively.
Skewness is mainly used to characterize the asymmetry of the probability distribution. Generally speaking, the skewness of the Rayleigh distribution is greater than the skewness of the Rice distribution. It is generally considered that the channel fading under LOS conditions obeys the Rice distribution, while the channel fading under NLOS conditions obeys the Rayleigh distribution. Therefore, the skewness in the NLOS environment is generally greater than the skewness in the LOS environment.

4. Average delay spread

$$\tau_{\text{mean}} = \frac{\sum_{n=0}^{N-1} \left|h(t_n)\right|^2 \tau_n}{\sum_{n=0}^{N-1} \left|h(t_n)\right|^2} \tag{8}$$

5. Root mean square (RMS) delay spread

$$\tau_{\text{rms}} = \sqrt{\frac{\sum_{n=0}^{N-1} (\tau_n - \tau_{\text{mean}})^2 \left|h(t_n)\right|^2}{\sum_{n=0}^{N-1} \left|h(t_n)\right|^2}} \tag{9}$$

Since the strongest single component (ie, LOS) does not exist in the NLOS channel, this often results in low power concentration in the delay. Therefore, generally speaking, the average delay spread and the root mean square delay spread in the NLOS environment are higher than those in the LOS environment.

6. Rise time

$$\tau_{\text{RT}} = \arg\max_{\tau} \left|h(t_n)\right| - \min(\tau_n) \tag{10}$$

The rise time is used to measure the time interval between the strongest component and the first component in the multipath signal. Under LOS conditions, the strongest component of the signal usually corresponds to the first component, while under NLOS conditions, the first component may be attenuated due to obstruction by objects or strong diffraction, making it usually before the strongest component. This results in a longer rise time. Therefore, the rise time in the NLOS environment is generally greater than the rise time in the LOS environment.

3.2 LOS identification algorithm

After extracting the channel characteristics from the CIR, a method needs to be used to identify the LOS path. Because the identification of LOS and NLOS can be regarded as a binary classification problem, this paper uses two different classification algorithms based on machine learning: GDBT and RF, to identify the LOS path, and their classification and recognition performance is compared. The two algorithms are briefly introduced below.

3.2.1 Gradient boosting decision tree

GBDT is an integrated learning method based on decision tree [22]. It uses the *classification and regression tree* (CART) algorithm, which can provide excellent classification and regression performance, has a reasonable complexity, and reduces the possibility of overfitting. Suppose $F(x)$ is an approximate function based on the response y of a set of predictor variables x. Since the output of the binary classification problem is a discrete sample category, we cannot fit the error of the sample output. To solve this problem, the log-likelihood loss function can be used, then the loss function can be expressed as

$$\mathcal{L}(y, F(x)) = \log(1 + \exp(-2yF(x))), y \in \{-1, 1\} \tag{11}$$

The GBDT algorithm uses the negative gradient of the loss function as an approximation of the residual, and then based on this value, we can construct a CART regression tree. Therefore, the negative gradient needs to be calculated first, which is

$$r_{ti} = -\left[\frac{\partial \mathcal{L}\left(y_i, F(x_i)\right)}{\partial F(x_i)}\right]_{F(x)=F_{t-1}(x)} \tag{12}$$

where $t = 1, 2, \ldots, T$ is the number of iterations, $i = 1, 2, \ldots, m$ is the number of samples.

Each training sample is divided into corresponding leaf nodes, and the best residual fitting value of each leaf node is

$$\gamma_{tj} = \arg\min_{\gamma} \sum_{x_i \in R_j} \log\left(1 + \exp\left(-2y_i(F_{t-1}(x_i) + \gamma)\right)\right) \tag{13}$$

where $j = 1, 2, \ldots, J$ is the leaf area, R_{tj} is the leaf area corresponding to the t-th CART tree.

Since (13) is difficult to optimize, we generally use approximate values instead, as

$$\gamma_{tj} = \frac{\sum_{x_i \in R_{jj}} r_{ti}}{\sum_{x_i \in R_j} |r_{ti}|(2 - r_{ti})} \tag{14}$$

In order to prevent over-fitting and improve classification accuracy, GBDT applies learning rate factors ξ, $0 < \xi \leq 1$. Then the updated approximation function $F_j(x)$ can be expressed as

$$F_j(x) = F_{j-1}(x) + \xi \cdot \sum_{t=1}^{T} \gamma_{tj} I\left(x \in R_{tj}\right) \tag{15}$$

3.2.2 Random forest

The RF algorithm, similar to GBDT, is an ensemble learning method composed of multiple different decision trees using randomly selected features. RF classifiers usually have good robustness to overfitting, but also have excellent classification performance, moderate complexity, and relatively large feature size (that is, it can handle high-dimensional data) [26].

We also use the CART tree. Each decision tree in CART-RF divides the input samples based on the Gini coefficient of the input elements instead of the information entropy. The Gini coefficient is defined as

$$\mathrm{Gini}(\mathbf{x}) = \sum_{\mathcal{L}=1}^{\mathcal{N}} p_{\mathcal{L}}(1 - p_{\mathcal{L}}) = 1 - \sum_{L=1}^{\mathcal{N}} p_{\mathcal{L}}^2 \tag{16}$$

where $p_{\mathcal{L}}$ denotes the ratio of the samples x that have the label $\mathcal{L}$ and the total data $\mathbf{X}$, and $\mathcal{N}$ is the number of data categories. In the paper, each sample is either LOS or NLOS, thus $\mathcal{N}$ is 2. The Gini index of a given feature x of the input data $\mathbf{X}$ is calculated as

$$\mathrm{Gini}(\mathbf{X}, x) = \frac{\left|\mathbf{X}^{x<x'}\right|}{|\mathbf{X}|}\mathrm{Gini}\left(\mathbf{X}^{x<x'}\right) + \frac{\left|\mathbf{X}^{x>x'}\right|}{|\mathbf{X}|}\mathrm{Gini}\left(\mathbf{X}^{x>x'}\right), \quad x \in \mathbf{x} \tag{17}$$

where x' is the threshold used to separate the data $\mathbf{X}$.

We can obtain the optimal classification of feature x^* by minimizing the Gini index of x as follows:

$$x^* = \arg \min_{x \in \mathbf{x}, x'} \mathrm{Gini}(\mathbf{X}, x) \tag{18}$$

In order to perform LOS recognition, first set the label:

$$l_k = \begin{cases} +1, & \text{LOS} \\ -1, & \text{NLOS} \end{cases} \tag{19}$$

where $k = 1, 2, \ldots, K$, K is the number of positioning points.

Assuming that the feature set is $\{x_k\}$, adding labels $\{l_k\}$ to form a complete input data set, i.e., $\{x_k, l_k\}$. Half of the positioning points in the positioning points with LOS path and the positioning points without LOS path are selected for the training of the classifier, that is, the training set is $\{x_k, l_k\}, k = 1, 2, \ldots, K/2$, and the remaining half of the positioning points are used for testing.

Then, we use Scikit-learn (an integrated library for statistical calculations in Python) to train GBDT and RF, and use the trained model to classify the channels in the test data set.

4 Single base station hybrid positioning method

According to the result of LOS identification, we distinguish between LOS environment and NLOS environment. Then in different positioning environments, we use different positioning methods to make their advantages complementary to improve positioning accuracy.

4.1 Single-BS positioning in LOS environment

For the LOS environment, due to the LOS path, that is, the signal propagates in a straight line between the BS and the MS, the direction and distance information between the BS and the MS can be obtained more accurately at this time. Therefore, the positioning method based on distance measurement has higher positioning accuracy and more common applications. For the positioning method based on distance measurement, the prerequisite for achieving high-precision positioning is to estimate the required positioning parameters. Commonly used positioning parameters mainly include AOA and time delay.

Generally speaking, multiple BSs are required for positioning using a single parameter. To realize single-BS positioning, a joint estimation of AOA and time delay is required [27, 28]. Common joint parameter estimation methods include MUSIC algorithm and ESPRIT algorithm, etc. These methods are relatively simple to implement and have high positioning accuracy. The ESPRIT algorithm does not need to search for spectral peaks in space all the time like the MUSIC algorithm, so the calculation is small. Therefore, for the LOS environment, we use the ESPRIT algorithm to jointly estimate the AOA and time delay, and then extract the parameters of the LOS path, so as to realize the position estimation of the MS.

4.2 Single-BS positioning in NLOS environment

For the positioning environment where there is no LOS path, many scholars choose to use NLOS error mitigation technology to reduce the effects of NLOS error on positioning. However, this type of method generally requires no less than 3 BSs. When the number of BSs is insufficient, accurate positioning cannot be performed. Moreover, since the NLOS error will follow different distributions in different environments, it is impossible to model the NLOS error uniformly. In response to this problem, this section uses the abundant parameter information in the NLOS channel to propose a method of directly using the NLOS path for positioning. The advantage of this method is that it can meet the positioning of a single base station and can achieve a relatively good positioning effect.

In the positioning system model given in Fig. 1, the positions of the BS and the MS are $\mathbf{q} = [x_{\mathrm{BS}}, y_{\mathrm{BS}}]^T$ and $\mathbf{p} = [x_{\mathrm{MS}}, y_{\mathrm{MS}}]^T$ respectively, and the position of the i-th scatterer is $\mathbf{s}_i = [x_{si}, y_{si}]^T$. d_{1i} is the distance from the BS to the i-th scatterer, d_{2i} is the distance from the i-th scatterer to the MS, φ_i is the angle of departure, θ_i is the angle of arrival. Therefore, the position coordinate of the i-th scatterer is

$$x_{si} = x_{\mathrm{BS}} + d_{1i} \cdot \cos\varphi_i \tag{20}$$

$$y_{si} = y_{\mathrm{BS}} + d_{1i} \cdot \sin\varphi_i \tag{21}$$

According to the geometric relationship, the position coordinates of the MS can be expressed as

$$x_{\mathrm{MS}} = x_{si} + d_{2i} \cdot \cos\theta_i \tag{22}$$

$$y_{\mathrm{MS}} = y_{si} + d_{2i} \cdot \sin\theta_i \tag{23}$$

As can be seen from Fig. 1, the measured distance from the BS to the MS is

$$d_{\text{nlos},i} = d_{1i} + d_{2i} \tag{24}$$

Then, combining (24), (22) and (23) can also be expressed as

$$x_{\text{MS}} = x_{si} + (d_{\text{nlos},i} - d_{1i}) \cdot \cos\theta_i \tag{25}$$

$$y_{\text{MS}} = y_{si} + (d_{\text{nlos},i} - d_{1i}) \cdot \sin\theta_i \tag{26}$$

Then substituting the expression of the abscissa x_{si} of the scatterer position in (20) into (25), the distance d_{1i} from the BS to the scatterer can be obtained as

$$d_{1i} = \frac{x_{\text{MS}} - x_{\text{BS}} - d_{\text{nlos},i} \cdot \cos\theta_i}{\cos\varphi_i - \cos\theta_i} \tag{27}$$

Similarly, combining (24), (20) and (21) can also be expressed as

$$x_{si} = x_{\text{BS}} + (d_{\text{nlos},i} - d_{2i}) \cdot \cos\varphi_i \tag{28}$$

$$y_{si} = y_{\text{BS}} + (d_{\text{nlos},i} - d_{2i}) \cdot \sin\varphi_i \tag{29}$$

It can also be seen from the positioning model that the distance from the scatterer to the MS can be expressed as

$$d_{2i} = \sqrt{(x_{\text{MS}} - x_{si})^2 + \left(y_{\text{MS}} - y_{si}\right)^2} \tag{30}$$

Then substituting the expressions of x_{si} and y_{si} in (28) and (29) into (30), the distance d_{2i} from the scatterer to the MS can be obtained as

$$d_{2i} = \frac{R_{xi}^2 + R_{yi}^2}{2\left(R_{xi}\cos\varphi_i + R_{yi}\sin\varphi_i\right)} \tag{31}$$

where $R_{xi} = d_{\text{nlos},i} \cdot \cos\varphi_i + x_{BS} - x_{\text{MS}}$, $R_{yi} = d_{\text{nlos},i} \cdot \cos\varphi_i + y_{\text{BS}} - y_{\text{MS}}$.

Generally speaking, measurement errors will inevitably occur in the measurement process, and the existence of measurement errors will increase the positioning error. Due to the measurement error, (24) is generally not valid. Taking the measurement error into account, the measurement distance in the NLOS environment can be expressed as

$$d_{\text{nlos},i} = d_{1i} + d_{2i} + \varepsilon_i \tag{32}$$

where ε_i represents measurement error.

Therefore, the position estimation problem of the MS can be solved by minimizing the measurement error. We set the objective function as

$$\mathcal{L}(\mathbf{p}) = \sum_{i=1}^{L} \varepsilon_i^2 \tag{33}$$

In general, the propagation distance of the LOS path is smaller than the propagation distance of the NLOS path, i.e.

$$d_{\mathrm{los}} \leq \min\left\{d_{\mathrm{nlos},i}\right\}, i = 1, 2, \ldots, L \tag{34}$$

where $d_{\mathrm{los}} = \sqrt{(x_{\mathrm{MS}} - x_{\mathrm{BS}})^2 + \left(y_{\mathrm{MS}} - y_{\mathrm{BS}}\right)^2}$.

Therefore, the position estimation of the MS can be obtained by solving the optimization problem, and the optimization model is

$$\begin{aligned} &\min \mathcal{L}(\mathbf{p}) \\ &\text{s.t.} \quad d_{\mathrm{los}} \leq \min\left\{d_{\mathrm{nlos},i}\right\}, i = 1, 2, \ldots, L \end{aligned} \tag{35}$$

Equation (35) is a nonlinear constrained optimization problem, and we use the genetic algorithm [29–31] to solve it.

4.2.1 Genetic algorithm

Genetic algorithm is an evolutionary algorithm that simulates the natural evolution process of organisms to find the optimal solution. Its main advantage is that it can automatically adapt to the global search space, and its global optimization capability is better. According to the model established by (35), the steps to solve it using genetic algorithm are as follows:

(1) Chromosome coding

When solving the optimization problem of the MS position, the chromosome coding scheme needs to be established first. We adopt the binary coding scheme, and by setting the population size and coding length, a random initial population can be obtained. Each row vector of the population, that is, each individual is a chromosome. Then, an appropriate decoding process is performed according to the given approximate position range of MS, and then the initial MS position corresponding to each chromosome can be obtained.

(2) Fitness function

Genetic algorithm judges the pros and cons of individuals according to their fitness, so as to select individuals that can be inherited to the next generation. From (34), we can see that the value of the objective function is always non-negative. And our optimization goal is to solve the minimum value of the function, so the reciprocal of the objective function value is used as the fitness of the individual.

Given the initial optimal fitness value *bestinti*, and then at each iteration, the fitness value *bestv* of each individual is obtained, and $bestv \geq bestinit$ is used as the judgment condition to judge the fitness value of the individual. Output the individual satisfying the condition and its corresponding optimal solution. If not, proceed to the next step.

(3) Selection function

The selection operation of genetic algorithm refers to the use of a certain method to eliminate individuals with low fitness from the parent population, retain individuals with high fitness, and inherit them into the next generation population.

For the selection operation, we use the best retention selection algorithm. The algorithm first selects individuals according to the method of roulette selection. Assuming that the total number of individuals in the group is N, the roulette wheel is divided into N sectors, and if the fitness of individual x_i is $f(x_i)$, the probability of it being selected is

$$p(x_i) = \frac{f(x_i)}{\sum_{i=1}^{N} f(x_i)} \tag{36}$$

Then use a random number r to simulate the rotation of the roulette, and compare the random numbers r and $p(x_i)$. If $r \le p(x_i)$, then chromosome x_i is selected, and so on, repeating N "rotations", then N chromosomes can be selected to form a new population. For the newly generated population, the complete structure of an individual with the highest fitness is retained, that is, it is copied directly to the next-generation population without performing subsequent genetic operations to achieve "best retention".

(4) Chromosome crossover

The crossover operation of the genetic algorithm refers to the exchange of certain genes in the two parent chromosomes in a certain way, and then recombination to form two new chromosomes. We use the single-point crossover operator in this paper. First select two chromosomes X and Y, and randomly generate a position q within their length range, and then exchange the codes at position q in chromosome X and chromosome Y to generate new chromosome X' and chromosome Y'. Since the offspring genes after the crossover may not meet the constraints or are duplicated, the parent chromosomes are not changed at this time, that is, the crossover operation is not performed, and the parent chromosomes directly enter the offspring, so the chromosomes before the crossover also need to be saved.

(5) Chromosome variation

The mutation operation of genetic algorithm means that the genes of new individuals formed by crossover may mutate, and then new individuals will be formed. We choose the simplest locus mutation, generate a random number $r \in [0, 1]$ for each individual bit after the crossover operation, set the mutation probability to p_m, if $r \le p_m$, then reverse the bit, otherwise the bit remains unchanged. Since the mutated offspring genes may not meet the constraints or are duplicated, the mutation fails at this time, and it needs to be mutated again until it succeeds.

4.2.2 Adaptive genetic algorithm

There are some problems with the basic genetic algorithm, such as:

1. The algorithm may converge prematurely in the early stage of the population evolution process and fall into a local optimal solution;
2. In the process of algorithm evolution, close relatives may occur;
3. The search efficiency of the algorithm in the later stage of evolution is low, and it needs to pass more iterative calculations to discard a large number of chromosomes that do not meet the constraint conditions, so the calculation time is relatively long. In order to solve the above problems, this paper uses an *adaptive genetic* (AG) algorithm [32, 33]. The improvement of this algorithm to the basic genetic algorithm is mainly reflected in two aspects:

(1) Adaptive crossover probability The crossover probability p_c of the basic genetic algorithm is constant, while the adaptive crossover probability will continue to

adjust and change with the evolution process. We use the crossover probability adjustment function to flexibly adjust the crossover probability during the evolution of the population. When the fitness of most individuals in the group tends to be consistent, the crossover probability becomes larger, so that the population can maintain diversity in the early stages of evolution. When the fitness of most individuals in the group is relatively scattered, the crossover probability is reduced, so that the population can complete a detailed search in the later stage of evolution, thereby preventing the optimal solution from being destroyed and accelerating the convergence speed. Define the adaptive cross-probability adjustment function as

$$p_c = \begin{cases} p_{c\max} - \frac{p_{c\max} - p_{c\min}}{1+(T-t)\frac{f-f_{\text{avg}}}{f_{\max}-f_{\text{avg}}}}, f \geq f_{\text{avg}} \\ p_{c\max}, f < f_{\text{avg}} \end{cases} \tag{37}$$

where $p_{c\max}$ is the maximum value of the crossover probability p_c, $p_{c\min}$ is the minimum value of p_c, T is the total generation number of the group, t is the current group generation number, f is the individual fitness of the current group, $f_{\max}$ is the maximum fitness of individuals in the group, and f_{avg} is the average fitness of individuals in the proup. It can be seen that the improved crossover probability p_c is adaptively adjusted and changed within the interval $[p_{c\min}, p_{c\max}]$.

(2) Adaptive mutation probability The mutation probability p_{m} of the basic genetic algorithm is also fixed. If the mutation probability is too small, premature maturity is prone to occur. Therefore, in the early stage of the evolution process, individuals in the group can use a larger mutation probability to mutate, so that the population can maintain diversity. However, if the mutation probability is too large, the optimal solution will be easily destroyed. Therefore, in the later stage of the population evolution, the mutation probability can be increased to speed up the convergence speed of the genetic algorithm and prevent the optimal solution from being destroyed. Similarly, we use the mutation probability adjustment function to flexibly adjust the mutation probability. Define the adaptive mutation-probability adjustment function as

$$p_{\text{m}} = \begin{cases} p_{\text{m}\max} - \frac{p_{\text{m}\max} - p_{\text{m}\min}}{1+(T-t)\frac{f-f_{\text{avg}}}{f_{\max}-f_{\text{avg}}}}, & f \geq f_{\text{avg}} \\ p_{m\max}, & f < f_{\text{avg}} \end{cases} \tag{38}$$

where $p_{\text{m}\max}$ is the maximum value of the mutation probability p_{m}, $p_{\text{m}\min}$ is the minimum value of p_m. It can be seen that the improved mutation probability p_{m} is adaptively adjusted and changed within the interval $[p_{\text{m}\min}, p_{\text{m}\max}]$.

4.3 Single-BS hybrid positioning algorithm based on LOS identification

Figure 2 shows the overall structure of the proposed hybrid positioning algorithm. First, we use the LOS identification algorithm to judge whether there is a LOS path in the environment. Then, according to the result of LOS identification, we adopt different positioning methods for different positioning environments. For the environment where there is a LOS path, we use the ESPRIT algorithm to jointly estimate the AOA and time delay of the LOS path to achieve position estimation. For the environment where there is no LOS path, we propose a single-base station positioning method that directly uses the

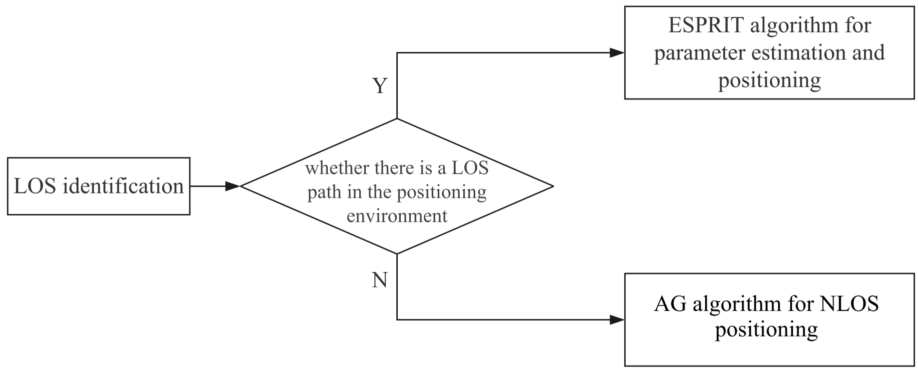

Fig. 2 Structure model of hybrid positioning algorithm based on LOS identification

NLOS path for positioning. The final position of the MS can be obtained by solving the optimization problem.

5 Experimental simulation results

In this section, the LOS identification results and the positioning results in different environments are simulated and verified. First, the LOS identification accuracy using different classifiers and different features is obtained through simulation. Then, the performance of the proposed single-base station positioning algorithm in the NLOS environment is verified for positioning points where there is no LOS path. And then, in order to prove that the hybrid positioning method proposed in this paper can complement the advantages of the two single positioning methods, that is, different positioning methods have different effects in different environments, the positioning results of the two methods in the LOS environment and the NLOS environment were compared. Finally, the simulation analysis of the hybrid positioning algorithm based on LOS identification proposed in this paper is carried out to prove its effectiveness.

We use statistical modeling to establish a mmWave MIMO positioning model, and generates two sets of positioning data to simulate two different propagation environments, LOS and NLOS. One group is that there are 1 LOS path and 2 NLOS paths between the BS and the MS, indicating the LOS environment. The other group is that there are only 3 NLOS paths between theBS and the MS, indicating the NLOS environment. Set the simulation experiment area to 10 m $\times$ 10 m, the signal center frequency $f_c = 60$ GHz, the number of BS antennas $M_t = 16$, the number of MS antennas $M_r = 16$, the bandwidth $B = 100$ MHz, the frequency interval $\Delta f = 240$ KHz, the number of subcarriers $N = 256$, the number of sampling points $N = 100$, the number of paths between BS and MS $L = 3$.

5.1 LOS identification result

We first use a single feature for LOS identification, and the single feature identification accuracy results obtained by using the GBDT and RF classifiers are shown in Table 1.

As can be seen from Table 1, first of all, for the GBDT and RF classifiers, the classification performance is almost the same. For a single feature, the identification accuracy of the total energy of the received signal ε is the highest, reaching 87.14%, followed by the rise time τ_{RT}, and the recognition accuracy rate is 78.39%. For kurtosis κ and skewness

Table 1 Single feature identification accuracy

Feature set	GBDT (%)	RF (%)
ε	87.14	86.25
κ	58.75	60.25
s	61.07	62.68
τ_{mean}	70.25	69.84
τ_{rms}	68.04	68.39
τ_{RT}	78.39	76.32

Table 2 Multiple features identification accuracy

Feature set	GBDT (%)	RF (%)
$\tau_{\text{mean}} + \tau_{\text{rms}} + \tau_{\text{RT}}$	85.89	87.28
Other features except ε	92.14	89.82
All six features	96.96	95.69

s, their identification accuracy is relatively low, only 60.25% and 62.68% respectively. The identification accuracy of the two features, the average delay spread τ_{mean} and the root mean square delay spread τ_{rms}, are 70.25% and 68.39% respectively, indicating that their identification performance is average. Therefore, the two characteristics of ε and τ_{RT} play a more important role in LOS identification.

Although single features such as ε and τ_{RT} can achieve relatively good LOS identification, their identification accuracy still cannot exceed 90%, and most of the features play a general role in LOS recognition. Therefore, it is still unable to obtain high identification accuracy. In this case, we use GBDT and RF classifiers to synthesize multiple features for LOS identification, because these two classification methods are ensemble learning methods, and both can merge multiple weak learners to achieve high-precision classification performance. Table 2 shows the accuracy results of multiple feature recognition by using GBDT and RF classifiers.

It can be seen from Table 2 that the identification accuracy of using multiple features is much higher than that of using a single feature, and the more the number of features used, the higher the identification accuracy. When all six features are used, the identification accuracy of GDBT and RF are 96.96% and 95.69%, respectively. Therefore, we choose to use GBDT's identification results for all six features, that is, a recognition accuracy of 96.96% as the basis for subsequent positioning work.

5.2 Positioning results of single-BS positioning method in NLOS environment

In this section, we have performed a simulation analysis on the performance of the proposed single-base station positioning method in the NLOS environment. We use the basic genetic algorithm and the adaptive genetic algorithm to solve the optimization model, and the positioning results are shown in Fig. 3.

It can be seen that when the genetic algorithm is used, the positioning error of 85% of the positioning points can be less than 1 m, and when the adaptive genetic algorithm is used, the positioning error of about 96% of the positioning points can be kept below 1 m.

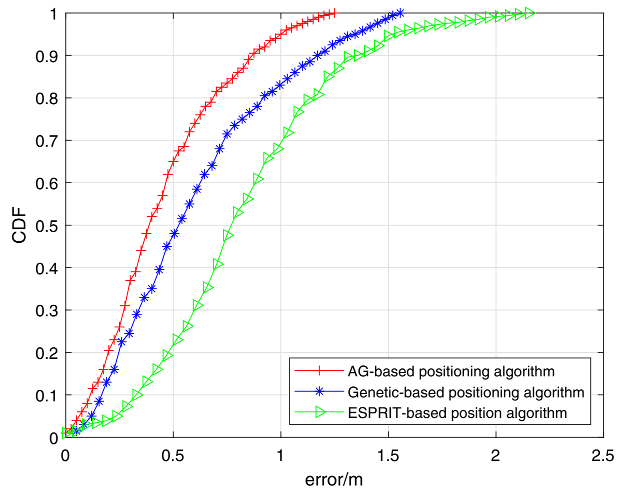

Fig. 3 Comparison of positioning results between different positioning algorithms in NLOS environment

Compared with the basic genetic algorithm, the positioning accuracy has been greatly improved. This is because the basic genetic algorithm will fall into the local optimal solution in the iterative process and produce certain errors. The simulation results also show that the adaptive genetic algorithm has greatly improved on this problem. The simulation results prove that the method of directly using the NLOS path for positioning proposed in this paper can also achieve better positioning results in the case of a single base station.

5.3 Comparison of positioning results in LOS and NLOS environments

In order to prove that the proposed hybrid positioning method can complement the advantages of the two single positioning methods, that is, different positioning methods have different effects in different environments, we compare the positioning results of the two methods in the LOS environment and the NLOS environment.

Figure 4 shows the comparison of the positioning results of the ESPRIT algorithm and adaptive genetic algorithm in LOS and NLOS environments. It should be stated that the performance of adaptive genetic algorithm in LOS environment is almost the same as that it in NLOS environment, so we only show one curve of adaptive genetic algorithm in the figure. It can be seen that in the LOS environment, both the ESPRIT algorithm and the adaptive genetic algorithm can achieve better positioning results, but the positioning accuracy of the ESPRIT algorithm is slightly better than that of the adaptive genetic algorithm. It is proved that for the LOS environment with LOS path, the positioning method using ESPRIT algorithm for parameter estimation is reasonable. In the NLOS environment, the positioning result of the adaptive genetic algorithm is significantly better than that of the ESPRIT algorithm. Because the signal in the NLOS environment is interfered by the reflection path during transmission, the ESPRIT algorithm is used to estimate the AOA and time delay will have a large error, while the direct use of the NLOS path for positioning will not have this problem. The simulation result also proves that it is better to use the NLOS path directly and use the adaptive genetic algorithm to solve the MS position in the NLOS environment.

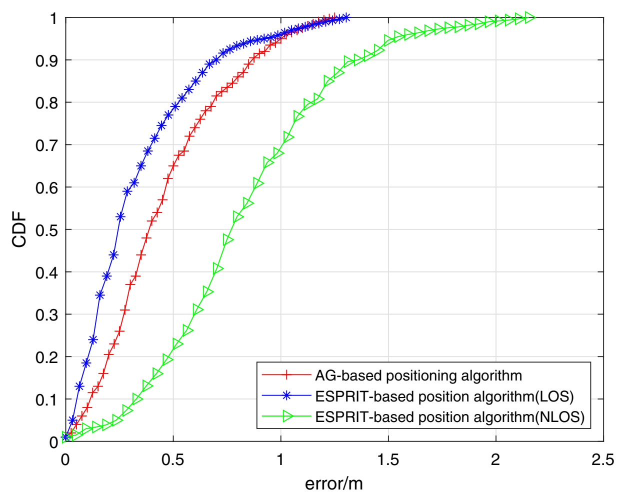

Fig. 4 Comparison of positioning results between ESPRIT algorithm and adaptive genetic algorithm

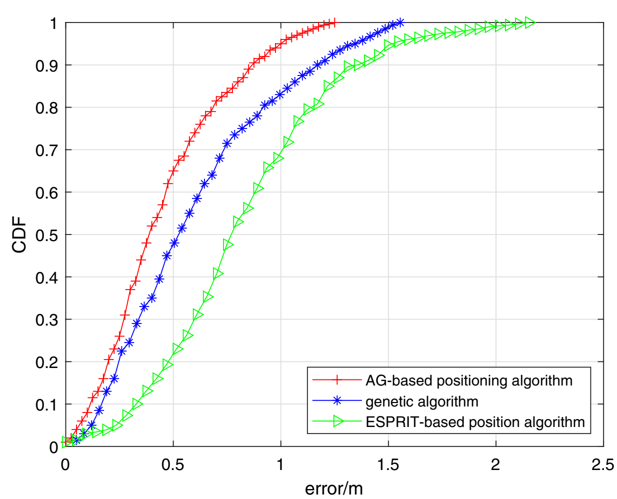

Fig. 5 Hybrid positioning results based on LOS identification

5.4 Hybrid positioning results based on LOS identification

To verify the performance of the proposed hybrid positioning method, we simulated two comparison groups. One group is to use ESPRIT algorithm to estimate the parameters of AOA and delay for all positioning points, consider the path with the shortest arrival time as the LOS path, and then extract the AOA and delay of the LOS path for positioning. The other group is to directly use their NLOS path to locate all the positioning points. Comparing the positioning results of the hybrid positioning method with the positioning results of the two comparison groups, the simulation results are shown in Fig. 5.

It can be seen that the positioning results using only the ESPRIT algorithm for parameter estimation are not ideal, because this type of method has a strong dependence on the propagation environment. The positioning result directly using the NLOS path for positioning is better than the positioning result using only the ESPRIT algorithm. This is because all the positioning points have the NLOS path, and this method has very low dependence on the propagation environment. Finally, combining LOS identification with the two methods, it can be seen that the positioning result of the proposed hybrid positioning method based on LOS identification is better than any single method, which proves the effectiveness of the proposed positioning scheme.

6 Conclusion

In this paper, we study the single-BS hybrid positioning algorithm based on LOS identification in mmWave systems. Aiming at the problem of complex and unpredictable positioning environment, we propose a hybrid positioning method based on LOS identification. First, we use the feature sets consisting of multiple features with different statistical distributions in LOS environment and NLOS environment, and use two classifiers, GBDT and random forest, to train the feature sets. After that, the trained model is used to classify the channels in the test set and judge whether there is a LOS path in the environment. Then, according to the result of LOS identification, we adopt different positioning methods for different positioning environments. For the environment where there is a LOS path, we use the ESPRIT algorithm to jointly estimate the AOA and time delay of the LOS path to achieve position estimation. For the environment where there is no LOS path, we propose a single-BS positioning method that directly uses the NLOS path for positioning. The final position of the MS can be obtained by solving the optimization problem. The advantage of this method is that it can satisfy single BS positioning and can achieve relatively high positioning accuracy. Simulation results prove that the proposed scheme can achieve high-precision positioning in a complex unknown positioning environment.

Abbreviations

BS	Base station
MS	Mobile station
LOS	Line of sight
NLOS	Not line of sight
GBDT	Gradient boosting decision tree
AOA	Angle of arrival
TOA	Time of arrival
ESPRIT	Estimation of signal parameters via rotation invariant technology
CIR	Channel impulse response
RF	Random forest
ULA	Uniform linear array

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Author contributions
All authors made contributions in the discussions, analyses and implementation of the proposed solution. X. Dou and Z. Jiao contributed to writing the manuscript. All authors read and approved the final manuscript.

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Declarations

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The authors declare that they have no competing interests.

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