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A TDOA and PDR Fusion Method for 5G Indoor Localization Based on Virtual Base Stations in Unknown Areas

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ABSTRACT Indoor positioning and navigation is an essential field of location-based service. Non-line of sight (NLOS) error restricts the accuracy of indoor positioning. Many researchers have studied the localization problem in indoor NLOS environments, but there is still a problem that NLOS error cannot be mitigated in unknown areas. To solve the above problems, this paper proposes a method of constructing virtual base stations in unknown areas (UA-VBS), and presents the corresponding positioning algorithm to calculate the location of the user equipment. Firstly, the base stations are selected and the initial positioning is carried out. Then, multiple virtual base stations are constructed according to the user equipment positions in the first three steps. The LOS base stations and virtual base stations participate in the TDOA calculation together, and calculate the base stations' combination with the minimum residual and the corresponding positioning result. Finally, the pedestrian dead reckoning fusion weight is updated by the residual value, and the accurate positioning result in NLOS environment is obtained. Simulation and experimental results show that the proposed algorithm has high positioning accuracy and stability in NLOS environment.

INDEX TERMS Indoor localization, 5G positioning, non-line of sight, virtual base station.

I. INTRODUCTION

In recent years, with the rapid development of mobile communication technology, location-based service (LBS) is playing an increasingly important role in people's daily life. Indoor positioning and navigation, as an essential field of LBS, have received widespread attention. Different indoor positioning technologies have been proposed by researchers around the world, including Wi-Fi [1]–[3], Bluetooth [4]–[6], UWB [7]–[9], Pedestrian Dead Reckoning (PDR) [10]–[12], image [13]–[14], and mobile communication networks [15]–[17]. Among them, indoor positioning technology based on mobile communication network has the following advantages over other positioning technologies: 1. wide coverage 2. a unified standard 3. no need for additional positioning equipment and terminals. In the 5G standard [18] of release 16, the 5G Positioning Reference Signal (PRS) is defined, and it can provide Time Difference of Arrival (TDOA) measurements to meet the requirements of positioning services. However, the indoor environment is complex and the transmission of wireless signal in this environment is heavily obscured. The current deployment of mobile communication networks is still focused on meeting communication needs, so there is a mixed line-of-sight (LOS)/ NLOS environment. Non-line-of-sight base stations will cause a large error in TDOA results, thus leading to increased indoor positioning errors [19].

Currently, the commonly used methods for handling non-line-of-sight error in a mixed LOS/NLOS environment include the residual-based method [20]–[23], base station selection method [24]–[28], virtual base station method [29]–[31], and NLOS propagation model compensation [32]–[37], in which the residual-based method and base station selection method improve the positioning accuracy by removing the NLOS base station. The virtual base station method can construct a virtual base station by mirroring the NLOS base station on the transmitting wall, and the constructed virtual base station can be regarded as a LOS base

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station for the user terminal, so it can be guaranteed that there are enough base stations to locate UE accurately.

All of these methods can improve the positioning accuracy in mixed LOS/NLOS environments. However, the residual-based method and NLOS base station selection method cannot guarantee a sufficient number of LOS base stations for localization under the existing mobile communication network deployment conditions. In contrast the virtual base station and model compensation methods require an explicit knowledge of the signal propagation path to accurately construct a virtual base station or a NLOS propagation model, which has limitations in practical applications. Therefore, this paper proposes a method of creating a Virtual Base Station in Unknown Areas (UA-VBS) and presents a corresponding location solving algorithm to calculate the user equipment (UE) position. First, the base station is selected and the positive definite TDOA equation calculates the initial location of UE, and then multiple virtual base stations are constructed based on the UE locations in the first three steps, as shown in FIGURE 1. Both the LOS base station and the virtual base station are jointly involved in TDOA solving, and the base station combination with the smallest residual and the corresponding localization results are calculated. Finally, the PDR fusion weights are updated by the residual value to obtain the accurate localization result in LOS/NLOS environment.

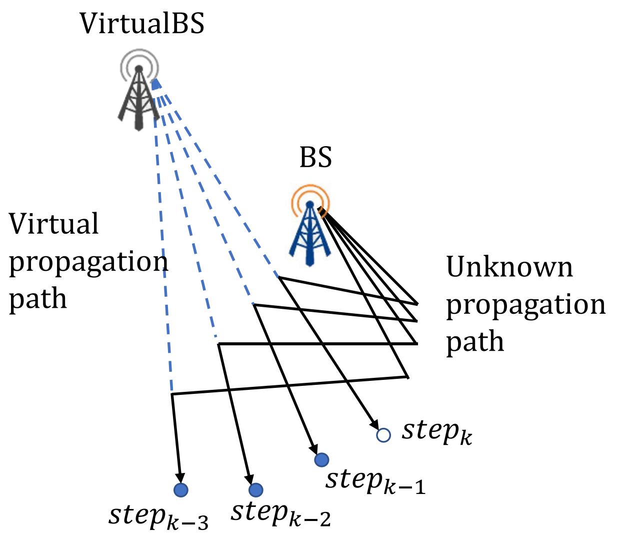

FIGURE 1. Schematic diagram of UA-VBS algorithm.

The fundamental difference between the proposed algorithm and the existing VBS algorithm is that the proposed algorithm does not need to know the prior information of the location environment. The existing algorithms of VBS need to know the location of obstacles in the positioning environment, the position of VBS is calculated by the positions of known obstacles and the real base station. The algorithm proposed in this paper is based on the measurements of NLOS BS to calculate the position of VBS in the process of positioning. It does not need to know the location of obstacles in the positioning environment, so it has higher practicability than the existing algorithms.

This paper is structured as follows: the first chapter is an introduction and introduces the background of the study. Chapter two is related work. Chapter 3 is the method, which describes the proposed algorithm in detail. Chapter 4 describes the simulations and experiments of UA-VBS and Chapter 5 is the conclusion.

II. RELATED WORK

In recent years, many researchers have conducted research on the positioning problem in NLOS environment, and the current mitigating methods for NLOS error are mainly divided into two categories: one is to exclude NLOS base stations to remove the influence of NLOS base stations on positioning results to improve positioning accuracy and the other is to process NLOS base station and compensate NLOS error by an algorithm. The NLOS base station is identified by the characteristics of signal or measurements in the first category method, and the influence of NLOS base station on the positioning result is removed in the position calculation. This kind of approach can effectively improve the positioning accuracy in the unknown area, but when the number of LOS base stations cannot meet the positioning requirements, it will still be affected by NLOS base stations.

For NLOS base station selection, Y. Xiaosheng [20] *et al.* proposed a voting matrix based on a residual weighting algorithm to mitigate NLOS error in indoor positioning, and updated the weights by calculating the residuals to achieve high-precision positioning in NLOS environments. L. Yan [21] *et al.* proposed a three-step positioning method to identify and mitigate the effects of NLOS by Bayesian Sequence detection and modified Kalman filter pre-process the signal and finally perform position estimation by residual weighting algorithm, which is an effective method to improve the positioning accuracy in NLOS environment. H. Luo [22] *et al.* proposed an iterative least residual method to alleviate NLOS error by calculating the residuals under different subsets of base stations to select the optimal subsets of base stations involved in localization, while using spatial correlation filtering to reduce the complexity of the iterative least residual method, which can reduce the computation time by 50%. W. Wang [23] *et al.* proposed a linear least-squares minimum residual algorithm to reduce NLOS error in the 3D indoor positioning environment, which is effective in improving positioning accuracy in NLOS environment. S. Bartelmaos [24] *et al.* proposed an RTT measurement method that takes NLOS error into account, which measures the best coherence between RTT estimates and three most reliable measurement methods are selected. This method was verified by simulation. L. Cheng [25] *et al.* proposed an improved NLOS error suppression algorithm based on residual weighting to gradually eliminate the effect of NLOS error on positioning in LOS transmission environment. In our previous study [26], we proposed a GDOP-assisted base station selection method based on channel conditions and GDOP value variation, which can effectively improve the positioning accuracy in a mixed NLOS/LOS environment. K. Han [27] *et al.*

proposed a low-complexity identification approach to identify the change in the channel situation between NLOS and LOS. Numerical experiment results indicate that the proposed algorithm has higher accuracy and is less impacted by NLOS errors than other conventional methods in mixed LOS and NLOS indoor environments. C. Jiang [28] *et al.* proposed a NLOS/LOS classification method based on deep learning method CNN-LSTM for positioning in mixed NLOS/LOS environments. The experiment result showed that the method has a better performance compared to the traditional classification method.

The second category method can model the propagation of NLOS base station or build virtual LOS base station according to NLOS base station and environment to compensate NLOS error. The advantage of this method is that it can ensure enough base stations to meet the positioning requirements, but it needs to model and analyze the environment in advance, so it is unable to carry out high-precision positioning in the unknown area.

For modelling compensation, D. Liu [29] *et al.* proposed a joint TOA and DOA virtual base station method to reduce NLOS error, and a two-step weighted least squares method fusing TOA and DOA for position estimation. Simulation results verified the effectiveness of the method. Y. Ma [30] *et al.* proposed a joint PDOA and AOA Virtual Base Station Location Method to establish virtual base stations to convert NLOS paths to LOS paths for passive positioning of UHF RFID. R. Zhang [31] *et al.* proposed a single base station method to generate virtual stations using a known floor plan of surrounding reflectors and a weighted least square (WLS) position estimator to calculate the location of the virtual stations, which has a better localization performance than multipath fingerprinting. S. Li [32] *et al.* proposed a statistical range error model in NLOS environment based on empirical range data, which substantially improved the localization accuracy and was tested in aircraft passenger cabins to achieve 99% seat-level accuracy. M. Yang [33] *et al.* introduced a transfer function to correlate the field at a given receiver with the field at the source as a function of frequency and location, which can effectively alleviate the NLOS effect. C. Hua [19] *et al.* proposed a multipath map (MPM) method based on the spatial domain modeling principle, which has good robustness in the reverse positioning framework. Meanwhile, an improved non-linear iterative algorithm with height component constrained which reduces the complexity is introduced to calculate the coordinates so that the performance of the MPM can be verified. S. Wu [34] *et al.* proposed a positioning algorithm in which the synchronization error and NLOS error are jointly modelled. The localization accuracy of the proposed algorithm is improved by more than 50% on average. K. Han [35] *et al.* established binary and improved multiple support vector classification models to realize NLOS intrusion detection and high-discrimination fingerprint localization, respectively. B. Cao [36] *et al.* employed Gaussian mixed model to re-estimate the measurement distance, and two parallel variational Bayesian adaptive Kalman filters under the structure of interacting multiple models were utilized to smoothen the result of GMM to eliminate the LOS and NLOS errors, respectively. G. Wang [37] *et al.* proposed to jointly estimate the source position and the NLOS error in the reference path. The proposed methods achieve superior performance over the existing techniques, as validated by using both simulated and experimental data.

The method based on base station selection does not require prior information about the environment. Still it can't obtain high-precision positioning results when there are not enough LOS base stations, the method based on model or VBS can obtain stable positioning results but requires prior information about the environment. The proposed method can construct a VBS without knowing the a priori information of the environment to achieve high-precision positioning in NLOS propagation environment.

III. PROPOSED METHOD

The structure of the method proposed in this paper is shown in FIGURE 2. Firstly, the base stations with small observation variance are sorted according to the variance of TDOA, and the LOS base stations are selected to calculate the initial position by the positive definite equation, and the UE's positions of the first three steps are calculated using PDR. Then, several virtual base stations are constructed according to the UE's locations of the first three steps. The LOS base stations and virtual base stations participate in the TDOA calculation together, and calculate the base stations' combination with the minimum residual and the corresponding positioning results. Finally, the PDR fusion weight is updated by the residual value, and the accurate positioning result in LOS/NLOS environment is obtained. Then, we will describe the UA-VBS method in detail.

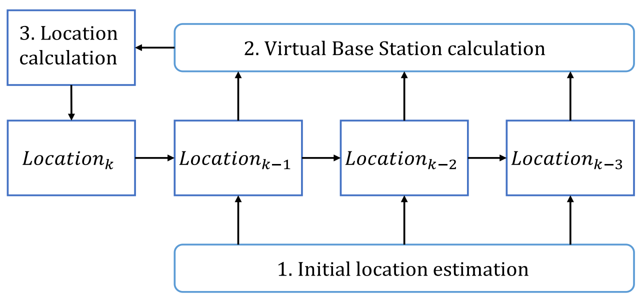

FIGURE 2. The structure of UA-VBS algorithm.

A. INITIAL LOCALIZATION

The base stations are ranked by the variance of the TDOA, which is calculated as follows:

$$s_i = \frac{\sum_{n=1}^{N}\left(R_{i,1}^{n} - \bar{R}_{i,1}\right)^2}{N-1}, \tag{1}$$

where s_i is the variance of the TDOA from the i-th base station, $R_{i,1}^{n}$ is the n-th TDOA measurement received by the UE from the i-th base station and the first base station. $\bar{R}_{i,1}$ is the mean of TDOA received by the UE from the i-th base station and the first base station. N is the total number of TDOA received from the same pair of base stations by UE. The purpose of (1) is to solve the variance of TDOA.

We can obtain the mean of the two TDOA with the smallest variance: $\bar{R}_{m,1}$ and $\bar{R}_{n,1}$, corresponding to m-th base station and n-th base station. According to the previous research on NLOS model, NLOS errors increase the mean and variance of the errors in range measurements [38]–[39]. Therefore, it is reasonable to use variance to select NLOS base stations. The following equation can be obtained,

$$\sqrt{(x_1-X_1)^2+(y_1-Y_1)^2} - \sqrt{(x_1-X_m)^2+(y_1-Y_m)^2} = \bar{R}_{m,1} \quad (2)$$

$$\sqrt{(x_1-X_1)^2+(y_1-Y_1)^2} - \sqrt{(x_1-X_n)^2+(y_1-Y_n)^2} = \bar{R}_{n,1} \quad (3)$$

where (x_1, y_1) is the positioning result of the first step, (X_1, Y_1) is the location of the first base station, (X_m, Y_m) is the location of m-th base station and (X_n, Y_n) is the location of n-th base station. The purpose of (2) and (3) is to calculate the initial positioning result.

Then the (2) and (3) are linearized.

$$(\bar{R}_{m,1})^2 + 2\bar{R}_{m,1}R_1 = K_m - 2X_{m,1}x_1 - 2Y_{m,1}y_1 - K_1 \quad (4)$$
$$(\bar{R}_{n,1})^2 + 2\bar{R}_{n,1}R_1 = K_n - 2X_{n,1}x_1 - 2Y_{n,1}y_1 - K_1 \quad (5)$$

where $K_1 = X_1^2 + Y_1^2$, $K_m = X_m^2 + Y_m^2$ and $K_n = X_n^2 + Y_n^2$. $X_{m,1} = X_m - X_1$, $Y_{m,1} = Y_m - Y_1$, $X_{n,1} = X_n - X_1$ and $Y_{n,1} = Y_n - Y_1$.

The (6) can be obtained by (4) and (5).

$$\begin{bmatrix} x \\ y \end{bmatrix} = -\begin{bmatrix} X_{m,1} & Y_{m,1} \\ X_{n,1} & Y_{n,1} \end{bmatrix}^{-1} \times \left\{ \begin{bmatrix} \bar{R}_{m,1} \\ \bar{R}_{n,1} \end{bmatrix} R_1 + \frac{1}{2} \begin{bmatrix} \bar{R}_{m,1}^2 - K_m + K_1 \\ \bar{R}_{n,1}^2 - K_n + K_1 \end{bmatrix} \right\} \quad (6)$$

where R_1 is

$$R_1^2 = (x_1 - X_1)^2 + (y_1 - Y_1)^2 \quad (7)$$

R_1 can be obtained by substituting (6) into (7), and the initial positioning result can be obtained by substituting R_1 into (6). Equation (4)-(7) is the process of solving (2) and (3). The positioning result of the first step can be solved by (1)–(7).

Calculate the variance of TDOA in the second step, and select the mean value of TDOA with the smallest variance $\bar{R}_{l,1}$, corresponding to the l-th base station.

$$\sqrt{(x_2-X_1)^2+(y_2-Y_1)^2} - \sqrt{(x_2-X_l)^2+(y_2-Y_l)^2} = \bar{R}_{l,1} \quad (8)$$

$$\sqrt{(x_2-x_1)^2+(y_2-y_1)^2} = l_{step} \quad (9)$$

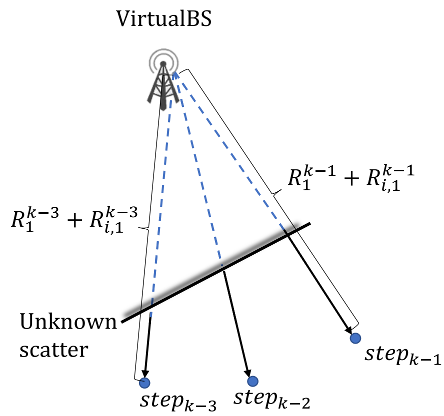

FIGURE 3. The method of constructing VBS.

where l_{step} is the step length of the current step. The purpose of equation (8) and (9) is to calculate the second step positioning results based on the PDR and TDOA, and (10)-(12) is used to solve the (8) and (9).

Then the (8) and (9) are linearized.

$$(\bar{R}_{l,1})^2 + 2\bar{R}_{l,1}R_1 = K_2 - 2X_{2,1}x_2 - 2Y_{2,1}y_2 - K_1 \quad (10)$$
$$R_1^2 - steplength^2 = X_1^2 - x_1^2 + Y_1^2 - y_1^2 + 2(x_1 - X_1)x_2 + 2(y_1 - Y_1)y_2 \quad (11)$$

The following equation can be obtained from (10) and (11).

$$\begin{bmatrix} x_2 \\ y_2 \end{bmatrix} = \begin{bmatrix} X_{2,1} & Y_{2,1} \\ x_1 - X_1 & y_1 - Y_1 \end{bmatrix}^{-1} \times \frac{1}{2} \times \begin{bmatrix} K_2 - K_1 + (\bar{R}_{l,1})^2 + 2\bar{R}_{l,1}R_1 \\ R_1^2 - len^2 - X_1^2 + x_1^2 - Y_1^2 + y_1^2 \end{bmatrix} \quad (12)$$

Substituting (10) and (11) into (7), the positioning result of the second step can be obtained, but there will be multiple solutions, which can be constrained by the heading angle of PDR to get the unique solution. The positioning result of the third step can be obtained by the same method.

B. CONSTRUCTION OF VIRTUAL BASE STATIONS

The method of constructing a virtual base station can be shown in FIGURE 3. For each NLOS base station received at k-th step, a VBS can be constructed, and we describe the process of constructing VBS below using the VBS corresponding to the i-th base station received by the UE as an example. R_i^k is the Time of Arrival of i-th base station in k-th step. Based on the positioning results and observation measurements in k-3 to k-1 steps, the following equations can be obtained:

$$(R_1^{k-3} + R_{i,1}^{k-3})^2 = (X_{VBS} - x_{k-3})^2 + (Y_{VBS} - y_{k-3})^2 \quad (13)$$
$$(R_1^{k-2} + R_{i,1}^{k-2})^2 = (X_{VBS} - x_{k-2})^2 + (Y_{VBS} - y_{k-2})^2 \quad (14)$$
$$(R_1^{k-1} + R_{i,1}^{k-1})^2 = (X_{VBS} - x_{k-1})^2 + (Y_{VBS} - y_{k-1})^2 \quad (15)$$

Equation (13)–(15) shows the relationship between k-3-th step to k-1-th step VBS locations and k-3-th step to k-1-th step UE measurements, respectively. Where (x_{k-3}, y_{k-3}) to (x_{k-1}, y_{k-1}) correspond to the location of the UE from k-3-th step to k-1-th step, respectively. R_1^{k-3} to R_1^{k-1} correspond to the calculated propagation time of the UE and the reference BS from *k-3*-th step to *k-1*-th step, respectively, and $R_{i,1}^{k-3}$ to $R_{i,1}^{k-1}$ are the TDOA received from the *i*-th base station and the reference base station from step *k-3* to step *k-1*, respectively. The location of the virtual base station we constructed is (X_{VBS}, Y_{VBS}), Let $f(X, Y, x, y) = (X-x)^2 + (Y-y)^2$, carry out the first-order Taylor expansion of the above equations, and approximately express it as linear equations in the form of matrixes. And $\mathbf{p}^{VBS} = [X_{VBS}\ Y_{VBS}]^T$.

$$\boldsymbol{G\Delta p^{VBS}} = \boldsymbol{b} \tag{16}$$

where

$$\boldsymbol{\Delta p^{VBS}} = \begin{bmatrix} X \\ Y \end{bmatrix} - \begin{bmatrix} X_{q-1} \\ Y_{q-1} \end{bmatrix} \tag{17}$$

$$\mathbf{G} = \begin{bmatrix} \frac{\partial f(X_{q-1}, Y_{q-1}, x_{k-1}, y_{k-1})}{\partial X} & \frac{\partial f(X_{q-1}, Y_{q-1}, x_{k-1}, y_{k-1})}{\partial Y} \\ \frac{\partial f(X_{q-1}, Y_{q-1}, x_{k-2}, y_{k-2})}{\partial X} & \frac{\partial f(X_{q-1}, Y_{q-1}, x_{k-2}, y_{k-2})}{\partial Y} \\ \frac{\partial f(X_{q-1}, Y_{q-1}, x_{k-3}, y_{k-3})}{\partial X} & \frac{\partial f(X_{q-1}, Y_{q-1}, x_{k-3}, y_{k-3})}{\partial Y} \end{bmatrix} \tag{18}$$

And q is the number of iterations,

$$b = \begin{bmatrix} (R_1^{k-1} + R_{i,1}^{k-1})^2 - f(X_{q-1}, Y_{q-1}, x_{k-1}, y_{k-1}) \\ (R_1^{k-2} + R_{i,1}^{k-2})^2 - f(X_{q-1}, Y_{q-1}, x_{k-2}, y_{k-2}) \\ (R_1^{k-3} + R_{i,1}^{k-3})^2 - f(X_{q-1}, Y_{q-1}, x_{k-3}, y_{k-3}) \end{bmatrix} \tag{19}$$

According to the least square method, we can obtain $\Delta\mathbf{p}^{VBS}$:

$$\boldsymbol{\Delta p^{VBS}} = (\boldsymbol{G^T G})^{-1}\boldsymbol{G^T b} \tag{20}$$

The solutions of the nonlinear equations 13–15 can be updated from $\mathbf{p}_{q-1}^{VBS}$ to $\mathbf{p}_q^{VBS}$.

$$\boldsymbol{p_q^{VBS}} = \boldsymbol{p_{q-1}^{VBS}} + \boldsymbol{\Delta p^{VBS}} \tag{21}$$

Iterate over (20) and (21) until $\mathbf{p}^{VBS}$ converges. The $\mathbf{p}^{VBS}$ after convergence is the position of the virtual base station.

C. SOLUTION METHOD OF LOCATIONS

The number of virtual base stations is equal to the total number of base stations that can be received by UE minus the number of LOS base stations. The sum of the number of virtual base stations and LOS base stations is N_{BS}, for the convenience of description, we renumber the virtual base stations and LOS base stations. The coordinates of the virtual base stations and LOS base stations are (X_i, Y_i), $i = 1, 2, \ldots, N_{BS}$, the TDOA is $TDOA_{i,1}$.

By combining the virtual base station and the LOS base station, $C_{N_{BS}}^4$ combinations can be obtained. $C_{N_{BS}}^4$ positioning results are calculated by Chan algorithm [40], and the residual of each positioning result is calculated by the following equation.

$$Resiual_m = \sum_{j=2}^{4}\left(\left(\sqrt{(x_m - X_j)^2 + (y_m - Y_j)^2} - \sqrt{(x_m - X_{1,m})^2 + (y_m - Y_{1,m})^2}\right) - TDOA_{j,1}\right) \tag{22}$$

where $m = 1, 2, \ldots, C_{N_{BS}}^4$, (x_m, y_m) is the positioning result in the *m*-th combination and $(X_{1,m}, Y_{1,m})$ is the location of reference base station in the *m*-th combination. The combination with the minimum residual is selected as the positioning result, and the PDR fusion weight is updated by the residual value. The algorithm of the process is as follows:

Algorithm 1

Input: $\boldsymbol{Residual_m}$, step_length, Heading, $\boldsymbol{p_{k-1}}$
Output: $\boldsymbol{p_k}$
1: $\boldsymbol{Residual_{min}} \leftarrow \boldsymbol{min}(\boldsymbol{Residual_m})$;
2: $\boldsymbol{p_{temp}} \leftarrow \boldsymbol{arg}[\boldsymbol{min}(\boldsymbol{Residual_m})]$;
3: SWITCH $\boldsymbol{Residual_{min}}$;
4: CASE $\boldsymbol{Residual_{min}} > \mathbf{2}$
5: $\boldsymbol{p_k} = \boldsymbol{p_{k-1}} +$ [step_length × cos(Heading) step_length × sin(Heading)]$^{\boldsymbol{T}}$;
6: CASE $\mathbf{0.5} < \boldsymbol{Residual_{min}} \le \mathbf{2}$
7: $\boldsymbol{p_k} = \boldsymbol{KF}(\boldsymbol{p_{k-1}}, \mathbf{step_{length}}, \mathbf{Heading}, \boldsymbol{p_{temp}})$;
8: CASE $\boldsymbol{Residual_{min}} < \mathbf{0.5}$
9: $\boldsymbol{p_k} = \boldsymbol{p_{temp}}$;
10: END SWITCH
11: END

where the step_length is the step length obtained from PDR, and Heading is the heading angle obtained from PDR. $KF(*)$ means the Kalman Filter fusion method. And $\boldsymbol{p_k} = [x_k\ y_k]^T$ is the k-th step positioning result.

IV. SIMULATION AND EXPERIMENT

To validate the algorithm proposed in this paper, in this chapter, we perform simulation and experiment on the UA-VBS algorithm. Section 4.1 describes the setup of the simulation scenario, modelling of the simulation channel, and the simulation results, and in Section 4.2, we test the UA-VBS algorithm using a self-developed 5G positioning system in an indoor environment. In addition to the measurement error caused by the wireless channel, the quality of the UE also affects the positioning accuracy, so in the following simulations and experiments, the same quality of the UE is used for the acquisition of measurements, and the positioning results are obtained by different solving methods to verify the effect of different solving techniques for NLOS error.

A. SIMULATION

In this section, we perform a simulation verification of the proposed UA-VBS, and the simulation scenario uses the underground parking lot of the research building of Beijing University of Posts and Telecommunications (BUPT), and the wireless channel of the underground parking lot of the research building of BUPT is simulated using the ray-tracing method, where the simulation environment, base station location and UE travel route are shown in FIGURE 4. The transmit signal is the 5G positioning reference signal (PRS) conforming to 3GPP TS38.211 [18], and the TDOA measurements are carried out by phase tracking method at the UE to verify the positioning accuracy of UA-VBS in NLOS environment by comparing residual-based Chan algorithm (the combination of the four base stations with the smallest residual is selected, and then the Chan algorithm is used to calculate the location of UE), PDR only and residual-based Chan and PDR fusion method using Kalman Filter (PDR+Chan KF, residual-based Chan algorithm is used to estimate the absolute locations of UE, PDR is used to estimate the heading angle and step length of UE. Kalman filter is used to fusion the absolute locations, heading angle and step length.). The simulation parameters are shown in TABLE 1. In the simulation, the step length of PDR is set as a random distribution whose mean value is the real step length and variance is 0.15 m. The heading angle is set as a random distribution whose mean value is the actual heading angle and variance is 12 degrees (The variance of step length and heading angle are all obtained from the measured data in our previous study).

TABLE 1. The simulation parameters.

Parameters	Value
carrier frequency	3.5GHz
bandwidth	100MHz
Subcarrier spacing	30kHz
Transmit power	23dBm
Base station noise figure	5dB
UE noise figure	9dB

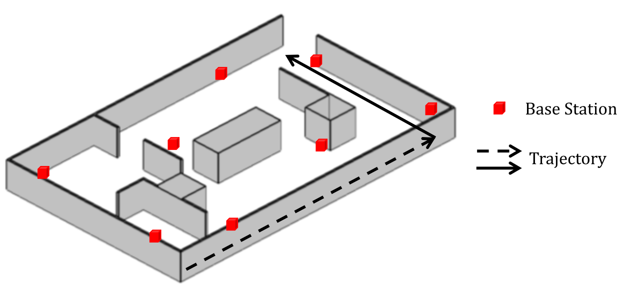

FIGURE 4. Simulation environment and locations of BSs.

FIGURE 5 shows the cumulative distribution function (CDF) diagram of the localization error for the UV-VBS algorithm, residual-based Chan, PDR only, and PDR + Chan KF in the above simulation scenario. And TABLE 2 shows the positioning error in the different probability of the methods above. It can be seen from the figure that UA-VBS has higher localization accuracy and stability compared to the other three localization algorithms. The positioning accuracy of the residual-based Chan algorithm is better than that of UA-VBS in about 65% cases, while the positioning accuracy of the residual-based Chan algorithm worsens sharply in 80%-100% probability. After analysis, it can be concluded that there are enough LOS base stations in 65% case of the simulation environment to obtain higher positioning accuracy by the residual-based method. For UA-VBS, the virtual base station is constructed despite the existence of sufficient LOS base stations, and since the construction of the virtual base station requires several adjacent steps to construct the localization results. The GDOP of the adjacent localization results is larger, resulting in the creation of the virtual base station error will be larger than the TDOA measurement error, so the localization error when introducing the virtual base station will be larger than the residual-based TDOA. In the other 35% of cases in the simulation environment, the number of LOS base stations cannot meet the positioning requirements, and NLOS base stations will be introduced to participate in the positioning solution, resulting in a sharp deterioration of the positioning results.

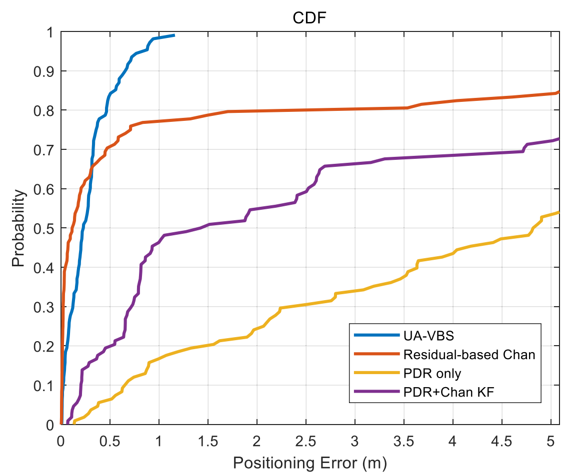

FIGURE 5. CDF of positioning error in simulation.

TABLE 2. Positioning error in the different probability of simulation.

Methods	50% Positioning Error (m)	65% Positioning Error (m)	80% Positioning Error (m)	90% Positioning Error (m)
UA-VBS	0.22575	0.31196	0.46268	0.64859
Residual-based Chan	0.11117	0.30421	1.701	7.2143
PDR only	4.8163	6.3121	6.7823	7.0113
PDR+Chan KF	1.4217	2.6391	8.3009	12.9461

FIGURE 6 shows the trajectories of the localization results of the UV-VBS algorithm, residual Chan, PDR only, and PDR + Chan KF in the above simulation scenario. It can be seen from FIGURE 6 that UA-VBS has higher localization accuracy and stability compared to the other three localization algorithms. In the figure, the red circles point to the locations that are greatly influenced by NLOS, and it can be seen that NLOS greatly influences the residual-based Chan and PDR + Chan KF in these regions, and the localization error is large.

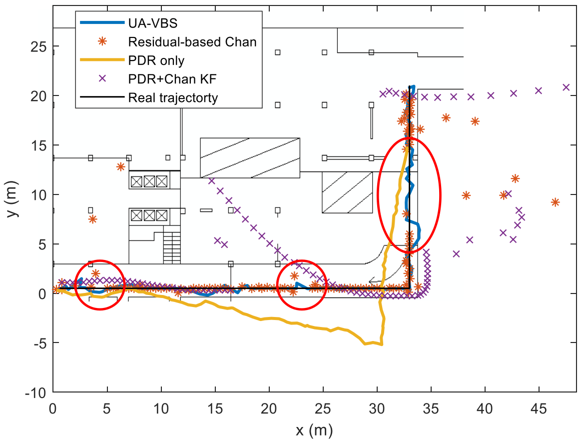

FIGURE 6. Trajectories of positioning results in simulation.

The UA-VBS algorithm proposed in this paper has stable and highly accurate localization results in these regions.

In the same simulation environment, we compare the proposed method with the state of the art methods. One is the NLOS positioning method based on VBS proposed by Zhang *et al.* [31], and the other is the NLOS location method based on base station selection proposed by Cheng *et al.* [25]. The results are shown in FIGURE 7. The simulation results show that the NLOS error positioning method based on VBS proposed by R. Zhang can provide a stable positioning result. In terms of the algorithm principle, the VBS location method proposed by R. Zhang should have similar positioning performance as the proposed positioning method in this paper. In contrast, the algorithm proposed in this paper does not need to know the prior information of the environment, and the method proposed by R. Zhang needs to know the prior information of the environment. However, it can be seen from the simulation results that the positioning performance of R. Zhang's method is generally weaker than that of the algorithm proposed in this paper. After analysis, it is concluded that the algorithm introduced PDR as an auxiliary to increase the positioning information and obtain higher positioning accuracy. The base station selection method proposed by L. Cheng can provide accurate positioning results in some cases, but when there are not enough LOS base stations to locate, the positioning performance is greatly reduced.

Since this algorithm needs to calculate the initial position and iterate the subsequent positioning results through the initial position, we simulate the positioning results under different initial position accuracy to verify the effect of different initial positioning accuracy on the overall positioning accuracy. The locations of step 2 and step 3 are obtained by PDR and TDOA, in other words, the estimation errors of the second and third steps are affected by the first step estimation error, PDR error and TDOA error. And the CDF of the UA-VBS algorithm positioning error under different initial positioning accuracy is shown in FIGURE 8. And TABLE 3 shows the positioning error in the different probability of the different initial error. It can be seen that UA-VBS can maintain high positioning accuracy when the initial positioning error

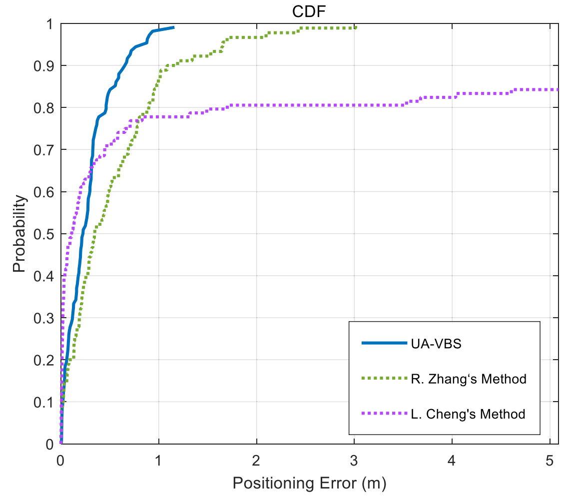

FIGURE 7. CDF of positioning error compared with the state of the art methods.

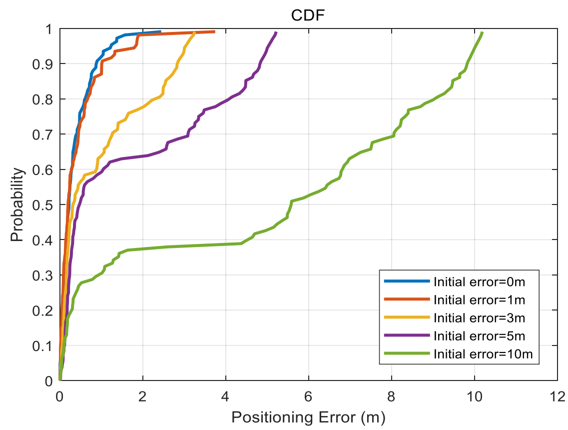

FIGURE 8. Positioning error in different initial positioning error.

TABLE 3. Positioning error in the different probability of different initial error.

Initial Error(m)	50% Positioning Error (m)	65% Positioning Error (m)	80% Positioning Error (m)	90% Positioning Error (m)
0	0.21669	0.31115	0.58957	0.87058
1	0.19211	0.38606	0.65491	1.0054
3	0.31151	1.0655	2.2194	2.825
5	0.46981	2.3823	4.038	4.8197
10	5.5762	7.2503	8.9878	9.8159

is within 3 meters, but the positioning accuracy worsens when the initial positioning error is 10 meters. FIGURE 9 is the trajectories of positioning results in different initial positioning error. From the trajectories of positioning results, it can be seen that when there are initial positioning errors, the errors of positioning results will gradually decrease, and eventually tend to higher positioning accuracy. It can be seen that although the initial positioning error has a significant impact on the algorithm, the positioning error will gradually decrease with the movement of UE.

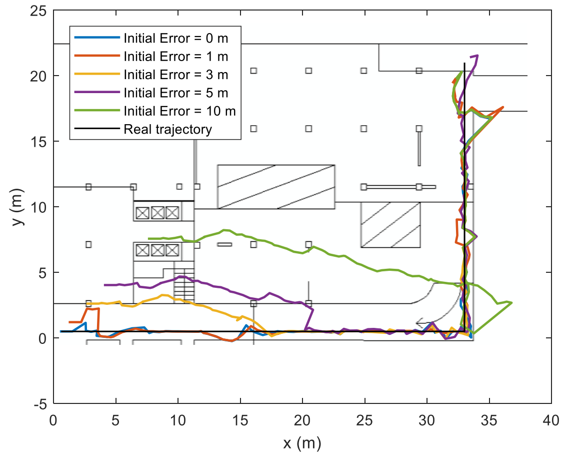

FIGURE 9. Trajectories of positioning results in different initial positioning error.

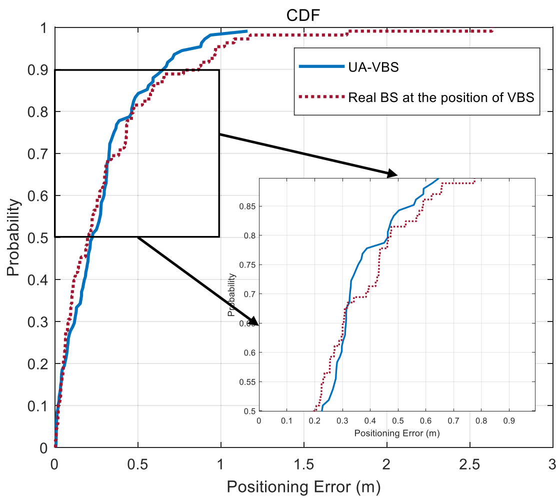

FIGURE 10. Error of positioning results obtained by placing a real base station at the VBS location.

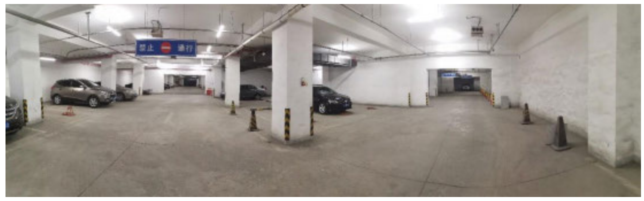

FIGURE 11. Experiment environment.

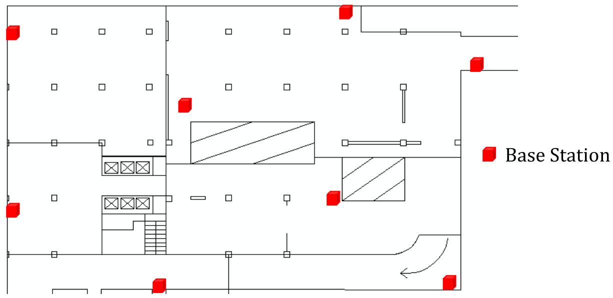

FIGURE 12. Map of the parking lot and locations of BSs.

FIGURE 13. Positioning UE.

To verify the accuracy of the VBS position estimation, we place real base stations at the calculated VBS positions, and then compare the simulation results in figure. It can be seen from the positioning results that the positioning results obtained by placing a real base station at the VBS location are similar to the positioning results calculated by this algorithm. This simulation proves the accuracy of the virtual base station location calculated by this algorithm.

B. EXPERIMENTS

In order to verify the usability of the proposed algorithm in practical applications, we set up an experimental environment in the parking lot on the first underground floor of the Beijing University of Posts and Telecommunications research building. We set up eight 5G positioning base stations in the parking lot on the first underground floor. The positioning UE is shown in FIGURE 13, and the positioning module in BS is shown in FIGURE 14. In addition to integrating the 5G signal processing module, the positioning UE also integrates a 9-axis inertial sensor.

The experimental results are shown in FIGURE 15 and FIGURE 16, where FIGURE 15 is the cumulative distribution function of the localization error for the UV-VBS algorithm, residual-based Chan, PDR only, and PDR + Chan KF, and FIGURE 16 is the trajectories of the localization results for the UV-VBS algorithm, residual-based Chan, PDR only, and PDR + Chan KF. And TABLE 4 shows the positioning error in the different probability of the methods above. It can be seen from the positioning results that the experiment results are highly similar to the simulation results. The positioning performance of the positioning method based on base station selection is better than the algorithm in 50% of the test points, because these test points have enough LOS base stations for high-precision positioning, and the positioning performance at about 50% of the test points is far worse than the proposed algorithm. This is because there are not enough LOS base stations at these test points for positioning, which leads to the introduction of NLOS error and large positioning error.

In the same experiment environment, we compare the proposed method with the state of the art methods mentioned

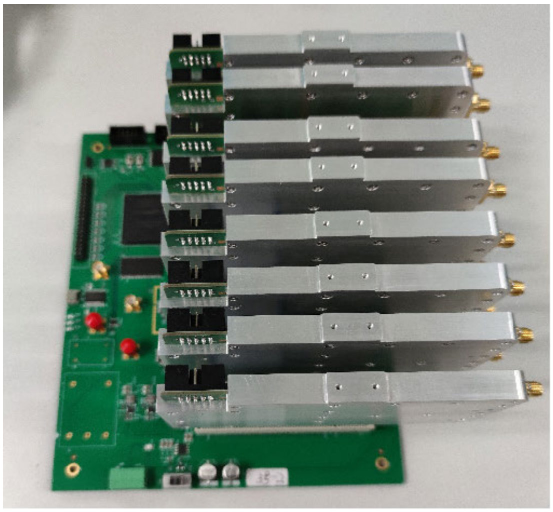

FIGURE 14. 5G positioning module in base station.

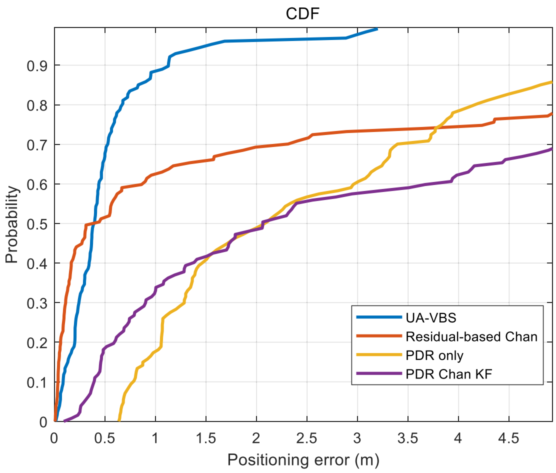

FIGURE 15. CDF of positioning errors in experiments.

TABLE 4. Positioning error in the different probability of experiment.

Initial Error(m)	50% Positioning Error (m)	65% Positioning Error (m)	80% Positioning Error (m)	90% Positioning Error (m)
UA-VBS	0.39719	0.47849	0.67625	1.1262
Residual-based Chan	0.44325	1.3394	5.6142	9.9129
PDR only	2.1041	3.2588	4.1905	5.6334
PDR+Chan KF	2.0615	4.4316	8.4239	24.821

in section 4.2. The results are shown in FIGURE 17. From the experimental results, we can see that the location method based on VBS proposed by R. Zhang has relatively stable positioning performance under the premise of a known positioning environment, while the positioning performance of L. Cheng's location method based on base station selection deteriorates rapidly in some cases. The experimental results also prove the correctness of the analysis of simulation results by section IV A and the accuracy of the algorithm in this paper Accuracy and stability.

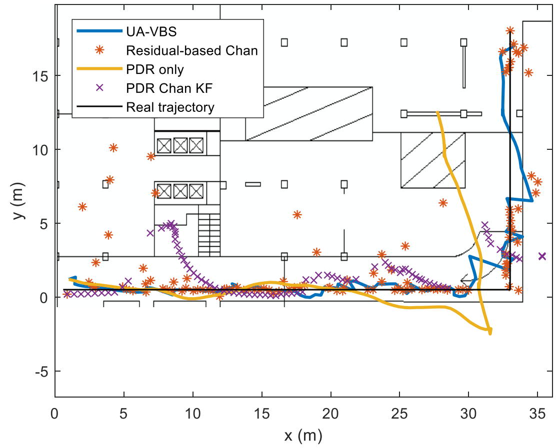

FIGURE 16. Trajectories of positioning results in experiments.

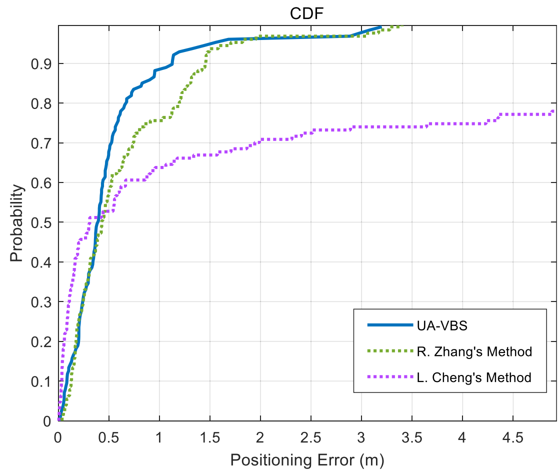

FIGURE 17. CDF of positioning error compared with the state of the art methods.

V. CONCLUSION

In this paper, we proposed an algorithm for constructing virtual base stations in unknown areas: UA-VBS. Firstly, the base stations are selected and the initial positioning is carried out. Then, multiple virtual base stations are constructed according to the UE positions in the first three steps. The LOS BS and VBS participate in the TDOA calculation, and calculate the BS combination with the minimum residual and the corresponding positioning result. Finally, the PDR fusion weight is updated by the residual value, and the accurate positioning result in NLOS environment is obtained. According to the simulations and experiments, it can be seen that the UA-VBS algorithm proposed in this paper has apparent advantages in coping with non-line-of-sight error in unknown areas, and can effectively improve the accuracy of 5G positioning indoors.

VI. FUTURE WORK

It can be seen from the experimental results that if the initial position error is large, it will take a period to stabilize the positioning results. Therefore, in future work, we will focus on how to obtain an accurate initial position and improve the stability of the algorithm.

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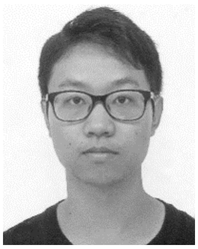

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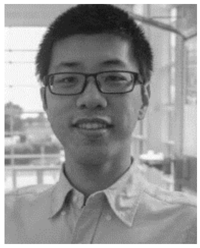

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