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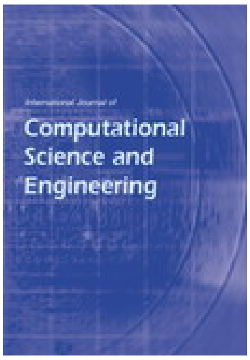

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Wireless optimisation positioning algorithm with the support of node deployment

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Abstract: Position is one of the basic attributes of an object, which is one of the key technologies for its collaborative operation. As a distributed sensing method, wireless sensor networks (WSNs) have become a feasible solution especially in satellite signal denied environments. Considering that the node deployment is the basis of target positioning in WSNs, this paper first researches optimal deployment of wireless nodes, and then researches the optimal positioning of mobile targets. Based on the least squares equation, a feature matrix that can characterise the positioning error is derived so that the positioning error caused by wireless node deployment is minimised. Following that, the positioning results are refined by particle swarm optimisation, which makes the mobile target have a coarse to fine accuracy. The results indicate that the proposed algorithm can reduce the influence of network topology on positioning error, which is critical for some location-based applications.

Keywords: distributed sensing; wireless positioning; node deployment; matrix eigenvalues; particle swarm.

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1 Introduction

1.1 Background

Target positioning relies on external sensor information or on its own sensors, which can use general or dedicated positioning algorithms to obtain real-time positions that characterise the motion of mobile targe. Positioning technology has been widely used in increasingly complex environments such as vehicle navigation, robot collaboration and logistics management. Only when a moving target accurately knows its position, it can accurately describe what happens at that position, and even drive multiple targets to move to a predetermined destination according to functional requirements (Lin et al., 2018). Positioning application scenarios can be mainly divided into enclosed and outdoor environments according to whether satellite signals can be obtained (Hadavi et al., 2019). For example, the satellite signals cannot be utilised in enclosed environments, such as indoor and underwater areas (An and Lee, 2019). In considerations of the increased requirements, accurate positioning technology is the basis of real-time tracking and navigation. Commonly, several base stations with known coordinates are deployed, and the mobile tags installed on the mobile targets are solved for their coordinates (Zhang et al., 2018). It is well known that wireless sensor networks (WSNs) are integrated with the advantage of intelligence, networking, and distribution, which can be widely used in some location-based applications (Chehri et al., 2009). There are many factors that affect WSNs positioning accuracy, such as node deployment strategies, wireless ranging methods, and positioning solution algorithms.

1.2 Related works

Many scholars have carried out a lot of researches on the optimisation of anchor node deployment through the Cramer-Rao lower bound (CRLB). Yang and Scheuing (2005) theoretically analysed CRLB based on TDOA localisation, and designed optimal sensor deployment based on minimising CRLB. Zhou et al. (2010) evaluated the positioning performance by studying the effect of landmark placement in rectangular regions, which illustrating that the optimal layout may vary with the aspect ratio of the geometry. Zhou et al. (2021) deduced the maximum posteriori probability estimation algorithm based on three-dimensional coordinate rotation, and obtained optimal deployment position of nodes that could satisfy the minimum trace time. Mei et al. (2021) obtained optimal deployment strategy through the closed-loop expression of the information matrix obtained by the particle idea. Chen et al. (2006) derived an upper bound for the linear least squares localisation error and found a landmark placement pattern that minimised the maximum localisation error based on the studied max L-min E algorithm. Liu et al. (2013) obtained optimal deployment model of beacons in a rectangular area by constructing the analytical relationship between the positioning error and Moore-Penrose pseudo-inverse matrix. Ji et al. (2007) compared the average uncertainty distances of the collinearity of the three beacons and obtained the optimal beacon deployment topology for an equilateral triangle. Although optimising the anchor node deployment strategy can improve the localisation performance, a better localisation algorithm is essential.

Considering the importance of localisation algorithms, some scholars have done a lot of research on various algorithms to improve positioning accuracy. Chan and Ho (2002) proposed a two-step weighted least squares algorithm for hyperbolic intersection location. Felus (2004) proposed a total least squares algorithm that considered both the observation vector and the data matrix errors. Huang (2020) proposed an optimised topology based on correlation neighbour graph, and proposed a DV-hop positioning algorithm with the hop number correction and average hop weighting. Shit et al. (2021) used a deep learning algorithm to match it with an updated radio map, and estimated the vehicle position from RSS samples. Zhao et al. (2022) proposed an improved weighted k-nearest neighbour combined with asymmetric Gaussian filtering algorithm for high-accuracy. Yin et al. (2019) proposed an edge-cloud co-positioning method that combines an edge-cloud structure, multiple distributed Kalman filters with a centralised cooperative fusion unit, which combined the advantages of both distributed and centralised positioning. Li et al. proposed a method to select anchor nodes using Gaussian selection method, and then use the square method to estimate the coordinates of unknown nodes. This method effectively improves the positioning accuracy (Huang et al., 2019). Zheng et al. proposed a localisation algorithm that does not require offline fingerprint collection, which can effectively deal with the failure of beacon nodes (Cai et al., 2017). Since both the anchor node deployment strategy and artificial intelligence can improve the positioning performance, it is particularly important to jointly optimise the anchor node deployment and the intelligent positioning algorithm of artificial intelligence.

1.3 Organisation of this paper

The remainder of this paper is organised as follows. In Section 2, we derive optimal deployment models for anchor nodes in 2D and 3D based on the analytical relationship between the localisation error of the least square algorithm and the pseudo-inverse matrix, so as to reduce the impact of anchor node deployment on the positioning accuracy. In Section 3, we use the particle swarm algorithm to refine the positioning results of the least squares algorithm under the condition of optimal deployment of anchor nodes, so as to reduce the influence of the ill-conditioned matrix in the least square algorithm on the positioning accuracy. In Section 4, the positioning results under different deployment strategies and different positioning algorithms are compared respectively. Section 5 concludes this paper.

2 Anchor node optimal deployment strategy

2.1 Anchor node 2D optimal deployment model

Anchor nodes and unknown nodes are deployed in the interested regions. The initially calibrated coordinate sets of anchor nodes are defined as $\boldsymbol{c}^o = [\boldsymbol{c}_1^o, \boldsymbol{c}_2^o, ..., \boldsymbol{c}_n^o]^T$, where $\boldsymbol{c}_i^o = [x_i^o, y_i^o, z_i^o]^T$, $i = 1, 2, ..., n$; The coordinate sets of unknown nodes are defined as $\boldsymbol{u}^o = [\boldsymbol{u}_1^o, \boldsymbol{u}_2^o, ..., \boldsymbol{u}_m^o]^T$, where $\boldsymbol{u}_j^o = \left[x_j^o, y_j^o, z_j^o\right]^T$, $j = 1, 2, ..., m$. The relationship of geometric distances among anchor nodes and unknown nodes can be expressed as

$$\begin{aligned} &\forall \left(\boldsymbol{c}_i^o, \boldsymbol{u}_j^o\right) \quad \exists i \in n, j \in m \\ &\text{s.t.} \quad \sqrt{\left(x_i^o - x_j^o\right)^2 + \left(y_i^o - y_j^o\right)^2 + \left(z_i^o - z_j^o\right)^2} \le R_c \end{aligned} \tag{1}$$

where R_c denotes the communication radius.

Wireless signals are applied to carry out ranging measurement. When the unknown node $\boldsymbol{u}_j^o$ is measured by the anchor nodes $\boldsymbol{c}_i^o$ and $\boldsymbol{c}_{i-1}^o$, the difference of geometric distance can be expressed as

$$\begin{aligned} d_{i,i-1}^{jo} &= \|\boldsymbol{c}_i^o - \boldsymbol{u}_j^o\| - \|\boldsymbol{c}_{i-1}^o - \boldsymbol{u}_j^o\| \\ &= v_s\left(t_{i,j} - t_{i-1,j}\right) \end{aligned} \tag{2}$$

where $d_{i,i-1}^{jo}$ represents the difference of geometric distance among unknown node $\boldsymbol{u}_j^o$, anchor nodes $\boldsymbol{c}_i^o$ and $\boldsymbol{c}_{i-1}^o$; $t_{i,j}$ denotes the propagation time between anchor node $\boldsymbol{c}_i^o$ and unknown node $\boldsymbol{u}_j^o$; $t_{i-1,j}$ denotes the propagation time between anchor node $\boldsymbol{c}_{i-1}^o$ and unknown node $\boldsymbol{u}_j^o$; v_s denotes the propagation speed of the wireless wave.

Unknown node coordinates can be solved using the wireless signals extracted from unknown nodes and anchor nodes. Within the communication radius R_c of unknown node $\boldsymbol{u}_j^o$, received $n-1$ arrival time differences can be used to establish the equations for estimating the coordinates of unknown node, which can be expressed as

$$\tilde{\boldsymbol{u}}_j = \left(\boldsymbol{A}^T\boldsymbol{A}\right)^{-1}\boldsymbol{A}^T\boldsymbol{b} \tag{3}$$

where $\tilde{\boldsymbol{u}}_j$ denotes the estimated coordinates of unknown node; $\boldsymbol{A} = 2\left[\left(c_2^o - c_1^o\right)^T; \left(c_3^o - c_2^o\right)^T; ...; \left(c_n^o - c_{n-1}^o\right)^T\right]$; $\boldsymbol{b} = \left[\rho_{2,1}^j, \rho_{3,2}^j, ..., \rho_{n,n-1}^j\right]^T$; $\rho_{i,i-1}^j = \boldsymbol{c}_i^{oT}\boldsymbol{c}_i^o - {\boldsymbol{c}_{i-1}^o}^T\boldsymbol{c}_{i-1}^o + {d_{i,i-1}^{jo}}^2 - 2d_{i,j}^o d_{i,i-1}^{jo}$; $d_{i,j}^o$ denotes the geometric distance between anchor node $\boldsymbol{c}_i^o$ and unknown node $\boldsymbol{u}_j^o$.

With the presence of multiple noises, the actual TDOA ranging can be modelled as $\tilde{d}_{i,i-1}^j = d_{i,i-1}^{jo} + \triangle d_{i,i-1}^j$, where $\triangle d_{i,i-1}^j$ refers to the ranging error, which obeys the Gauss distribution $N\left(0, \sigma_t^2\right)$.The positioning errors of unknown node $\boldsymbol{u}_j^o$ can be expressed as:

$$\|\tilde{\boldsymbol{u}}_j - \boldsymbol{u}_j^o\| = \|\boldsymbol{A}^+ \triangle \boldsymbol{d}\| \le \|\boldsymbol{A}^+\|\|\triangle \boldsymbol{d}\| \tag{4}$$

where $\boldsymbol{A}^+$ is the pseudo-inverse matrix of matrix $\boldsymbol{A}$, $\tilde{\boldsymbol{u}}_j = [\tilde{x}_j, \tilde{y}_j, \tilde{z}_j]^T$ refers to the estimated coordinates of the unknown node.

As for wireless TDOA ranging, at least four anchor nodes are installed to form a basic positioning unit. According to the number of anchor nodes, how to select an effective deployment strategy is critical for obtaining higher positioning accuracy. Considering that the singular value of matrix $\boldsymbol{A}$ is the eigenvalue square root of matrix $\boldsymbol{A}^T\boldsymbol{A}$, the positioning errors can be evaluated by the eigenvalue of matrix $\boldsymbol{A}^T\boldsymbol{A}$ (Ji et al., 2007). As the unknown nodes are deployed in the XOY plane, the unknown nodes are also located in the XOY plane, whose length and width are denoted as l and w. Without the Z axis coordinate, the matrix $\boldsymbol{A}_{XY}^T\boldsymbol{A}_{XY}$ can be expressed as

$$\boldsymbol{A}_{XY}^T\boldsymbol{A}_{XY} = 4\begin{bmatrix} \Lambda_{11} & \Lambda_{12} \\ \Lambda_{12} & \Lambda_{22} \end{bmatrix} \tag{5}$$

where

$$\begin{aligned} \Lambda_{11} &= \sum_{i=2}^{n} \left\|x_i^o - x_{i-1}^o\right\|^2, \\ \Lambda_{22} &= \sum_{i=2}^{n} \left\|y_i^o - y_{i-1}^o\right\|^2, \\ \Lambda_{12} &= \sum_{i=2}^{n} \left\|x_i^o - x_{i-1}^o\right\| \left\|y_i^o - y_{i-1}^o\right\|. \end{aligned}$$

The two eigenvalues λ can be calculated as

$$\lambda = \frac{\Lambda_{11} + \Lambda_{22} \pm \sqrt{\left(\Lambda_{11} - \Lambda_{22}\right)^2 + 4\Lambda_{12}^2}}{2} \tag{6}$$

The problem of minimum positioning error under optimal deployment can be transformed into the problem of maximising the smaller eigenvalue (Ji et al., 2007). In the interested regions $l \times w$, the positioning errors can be expressed as

$$\begin{aligned} &\max \quad \frac{\Lambda_{11} + \Lambda_{22} - \sqrt{\left(\Lambda_{11} - \Lambda_{22}\right)^2 + 4\Lambda_{12}^2}}{2} \\ &\text{s.t.} \quad 0 \le x_i^o \le l; \ 0 \le y_i^o \le w \end{aligned} \tag{7}$$

Obviously, in order to maximise the formula (7), the first task is to minimise Λ_{12}^2, and its minimum value is 0. Setting the coordinates of the first anchor node $\boldsymbol{c}_1^o$ as $[0, 0, 0]^T$, another two anchor nodes $\boldsymbol{c}_2^o$ and $\boldsymbol{c}_3^o$ can be set as $[l, 0, 0]^T$ and $[l, w, 0]^T$ along the rectangular edges, which can make the eigenvalue λ maximising. If the expression $\Lambda_{11} + \Lambda_{22}$ is the maximum, as well as the expressions $\Lambda_{11} - \Lambda_{22}$ and Λ_{12}^2 are the minimum, the eigenvalue λ is equal to w^2. The positioning errors have the minimum values if three anchor nodes are deployed as the isosceles right triangle. When there are four anchor nodes, the coordinates of the first anchor node $\boldsymbol{c}_1^o$ are set as $[0, 0, 0]^T$, the coordinates of anchor nodes $\boldsymbol{c}_2^o$, $\boldsymbol{c}_3^o$ and $\boldsymbol{c}_4^o$ can be set as $[l, 0, 0]^T$, $[l, w, 0]^T$ and $[0, w, 0]^T$ along the rectangular edges, which can make the eigenvalue λ maximising with w^2.

2.2 Anchor node 3D optimal deployment model

As the unknown nodes are deployed in the XYZ space, the unknown nodes are also located in the XYZ space, whose length, width and height are denoted as l, w and h. The matrix $\boldsymbol{A}^T\boldsymbol{A}$ can be expressed as

$$\boldsymbol{A}^T\boldsymbol{A} = 4\begin{bmatrix} \Lambda_{11} \, \Lambda_{12} \, \Lambda_{13} \\ \Lambda_{12} \, \Lambda_{22} \, \Lambda_{23} \\ \Lambda_{13} \, \Lambda_{23} \, \Lambda_{33} \end{bmatrix} \tag{8}$$

where

$$\Lambda_{13} = \sum_{i=2}^{n} \left\|x_i^o - x_{i-1}^o\right\| \left\|z_i^o - z_{i-1}^o\right\|,$$

$$\Lambda_{23} = \sum_{i=2}^{n} \left\|y_i^o - y_{i-1}\right\| \left\|z_i^o - z_{i-1}^o\right\|,$$

$$\Lambda_{33} = \sum_{i=2}^{n} \left\|z_i^o - z_{i-1}^o\right\|^2.$$

The eigenvalues of matrix $\boldsymbol{A}^T\boldsymbol{A}$ are λ_1, λ_2 and λ_3, respectively, $\lambda_1 \geq \lambda_2 \geq \lambda_3$. Obviously, when the three eigenvalues are equal, λ_3 takes the maximum value. According to $\sum_{i=1}^{3} \lambda_i = trace\left(\boldsymbol{A}^T\boldsymbol{A}\right)$, we can get

$$\lambda_3 = \frac{4}{3}(\Lambda_{11} + \Lambda_{22} + \Lambda_{33}) \tag{9}$$

Therefore, the 3D deployment optimisation problem of anchor nodes can be expressed as

$$\begin{aligned} &\max \quad \Lambda_{11} + \Lambda_{22} + \Lambda_{33} \\ &\text{s.t.} \quad 0 \leq x_i^o \leq l; \; 0 \leq y_i^o \leq w; \; 0 \leq z_i^o \leq h \end{aligned} \tag{10}$$

Through solving the Λ_{11}, Λ_{22}, and Λ_{33} to maximise the above formula, optimal deployment of anchor nodes can minimise the positioning errors. Because the coordinates of the x-axis, y-axis and z-axis are independent of each other, and $l \geq w \geq h$, we first deploy the abscissa of the anchor node, secondly consider the ordinate of the anchor node, and finally consider the height of the anchor node. When n is an even number, the abscissa of $n/2$ anchor nodes is set to 0, and the abscissa of other anchor nodes is set to l. When n is an odd number, and the abscissa of anchor node $\boldsymbol{c}_1$ is 0, the abscissa of $(n+1)/2$ anchor nodes is set to 0, and the abscissa of other anchor nodes is set to l. When n is an odd number, and the abscissa of the first anchor node $\boldsymbol{c}_1$ is l, the abscissas of $(n+1)/2$ anchor nodes are set to l, and z-axis directions is similar to the x-axis. Therefore all anchor nodes are deployed at the vertices of the cuboid.

3 Distributed positioning solutions

In the process of distributed solution, the ill-conditioned matrix will cause unpredictable positioning errors. Although it has the shortcomings of being easy to fall into the local optimum and premature convergence, particle swarm optimisation algorithm can be regarded as a powerful tool to optimise positioning accuracy (Osei-Kwakye et al., 2022). An improved particle swarm optimisation is proposed, which can improve the global search ability, prevent premature convergence and improve the positioning accuracy. The improved particle swarm optimisation mainly includes two steps: grouping and adaptive adjustment.

Step 1 Initialising the particle swarm

The primary estimation $\tilde{\boldsymbol{u}}_j$ can be used to generate the initial position $\boldsymbol{u}_p$ of the partial swarm. The initial position $\boldsymbol{u}_p$ of the partial swarm can be expressed as

$$\boldsymbol{u}_p = \tilde{\boldsymbol{u}}_j + \xi, p \in [1, ..., P] \tag{11}$$

where $\boldsymbol{u}_p = [x_p, y_p, z_p]^T$; ξ obeys the Gaussian distribution $N\left(0, \sigma_p^2\right)$; P refers to the number of particles.

Step 2 Selecting the fitness function

Wireless ranging can be affected by the measurement noises and calibration errors. The difference between the measured TDOA ranging $\tilde{d}_{i,i-1}^j$ and the expression $\left\|\boldsymbol{c}_i^o - \boldsymbol{u}_p\right\| - \left\|\boldsymbol{c}_{i-1}^o - \boldsymbol{u}_p\right\|$ is selected as the fitness function, which can be expressed as

$$\begin{aligned} &f\left(\boldsymbol{u}_p\right) \\ &= \sum_{i=1}^{n} \gamma_i \left(\left(\left\|\boldsymbol{c}_i^o - \boldsymbol{u}_p\right\| - \left\|\boldsymbol{c}_{i-1}^o - \boldsymbol{u}_p\right\|\right) - \tilde{d}_{i,i-1}^j\right) \end{aligned} \tag{12}$$

where γ_i is the weighting factor, which satisfies $\gamma_i = 1$ without any prior information.

Step 3 Updating the individual and group optimal values

The minimum fitness function value of the individual particle is taken as the individual optimal value $\boldsymbol{O}_p^t$ in the iterative process, and the particle position corresponding to the individual optimal value $\boldsymbol{O}_p^t$ is recorded. The minimum of the individual optimal values corresponding to all particles are taken as the group optimal value $\boldsymbol{O}_g^t$, the particle position corresponding to the group optimal value $\boldsymbol{O}_g^t$ is recorded.

Step 4 Grouping the particle swarm

To ensure the diversity of the particle swarm, the overall particles $f\left(\boldsymbol{u}_p\right)$ that are lower than or equal to the particle with the average fitness f_{avg} are divided into the subgroup g_L, while others are divided into the subgroup g_H (Wei et al., 2009).

Step 5 Updating the particle velocity and position

The velocity and position of the particles in the subgroups g_L and g_H need to be updated, and be used for finding the particle position with the smallest fitness. As for the subgroup g_L, the velocity and position can be updated as

$$\begin{aligned} \boldsymbol{v}_p^{t+1} &= \chi \boldsymbol{v}_p^t + \varphi_p^1 \left(\boldsymbol{O}_p^t - \boldsymbol{u}_p^t\right) + \varphi_p^2 \left(\boldsymbol{O}_g^t - \boldsymbol{u}_p^t\right) \\ \boldsymbol{u}_p^{t+1} &= \boldsymbol{u}_p^t + \boldsymbol{v}_p^{t+1} \end{aligned} \tag{13}$$

where χ denotes the inertia weight. The larger χ means the stronger global search ability, and the smaller χ means the stronger local search ability, which is set to 0.5 in this paper; φ_p^1 and φ_p^2 are random numbers between 0 and 2.5 respectively.

The subgroup g_H has the same velocity and position updating with subgroup g_L. The particles with relatively large fitness in subgroup g_H need to accelerate the convergence. The inertia weight needs to be adaptively adjusted according the different fitness, which can be expressed as

$$\chi = \frac{1}{1 + e^{-\alpha\left(f\left(\boldsymbol{u}_p^t\right) - 0.5(f_{\max} - f_{\min})\right)}} + \beta \tag{14}$$

where α and β are the control parameters; $f_{\max}$ and $f_{\min}$ are the maximum and minimum fitness in the subgroup g_H.

Step 6 Iterative loop

If the maximum iteration is not reached, return to Step 3; otherwise, the global optimal $\boldsymbol{O}_g^t$ corresponds to the particle position is set as the updated estimation $\tilde{\boldsymbol{u}}_j$ of mobile target.

4 Accuracy evaluation

In this section, we use MATLAB to conduct experimental simulations and evaluate the positioning performance under different deployments. Here we set the length l, width w and height h of the cuboid to 10 m, 10 m and 5 m respectively. The TDOA noise variance σ_t^2 is set to 0.2^2.The particle number P is set to 50. The variance σ_p^2 of ξ is 1^2. Parameters α and β are set to 0.8 and 0.3, respectively. 200 unknown nodes are randomly generated in this positioning area, and the positioning error of each unknown node is the average value of 100 Monte Carlo simulations. The positions of anchor nodes in random deployment are randomly generated. Shrink deployment is the shrink mode for optimal deployment. Optimal deployment is the deployment scheme mentioned in this paper. The algorithm proposed in this paper is compared with the Chan algorithm (Chan and Ho, 2002) and the TLS algorithm (Felus, 2004).

Figure 1 shows the positioning performance under different anchor node deployment modes with different anchor node numbers. When the number of anchor nodes is 4, the average positioning errors of random deployment, shrink deployment and optimal deployment are 0.90 m, 0.79 m and 0.65 m, respectively; when the number of anchor nodes is 5, the average positioning errors of these three deployment methods are 0.78 m, 0.54 m and 0.45 m respectively; when the number of anchor nodes is 6, the average positioning errors of these three deployment methods are 0.71 m, 0.45 m and 0.37 m, respectively; when the number of anchor nodes is 7, the average positioning errors of these three deployment methods are 0.56 m, 0.44 m and 0.36 m respectively; when the number of anchor nodes is 8, the average positioning errors of these three deployment methods are 0.44 m, 0.35 m and 0.30 m. Compared with random deployment, the positioning performance of optimal deployment is greatly improved. Compared with the shrink deployment, the performance of optimal deployment is improved by 20.6%. This is because the interior space edges of the overall topology under optimal deployment scheme are relatively large.

Figure 1 Positioning performance under different anchor node deployment modes with different anchor node numbers (see online version for colours)

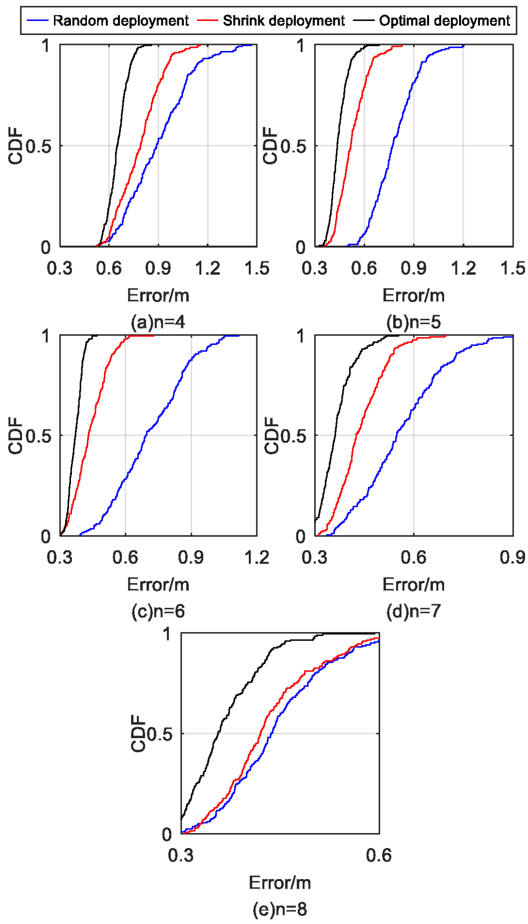
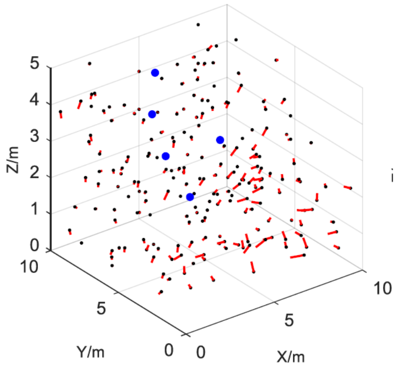
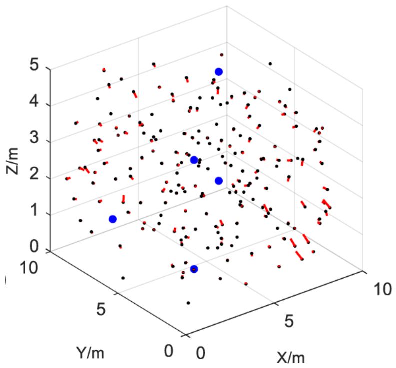


Figure 2 shows the positioning accuracy of unknown nodes under random deployment, shrink deployment and optimal deployment of five anchor nodes. The average positioning errors of random deployment, shrink deployment and optimal deployment are 0.78 m, 0.54 m and 0.45 m, respectively, of which the maximum positioning errors are 1.20 m, 0.83 m and 0.66 m, and the minimum positioning errors are 0.50 m, 0.38 m and 0.35 m, respectively. The positioning error of unknown nodes inside the topology structure of random deployment anchor nodes is generally small, the positioning error of external unknown nodes is large. For shrink deployment, the positioning errors of unknown nodes inside the anchor node topology and external nodes close to the anchor node topology are generally small, and the positioning errors of external unknown nodes far away from the topology structure are large. However, the overall positioning error of optimal deployment is small. It shows that the topology of the anchor node has a great influence on the positioning error in 3D positioning.

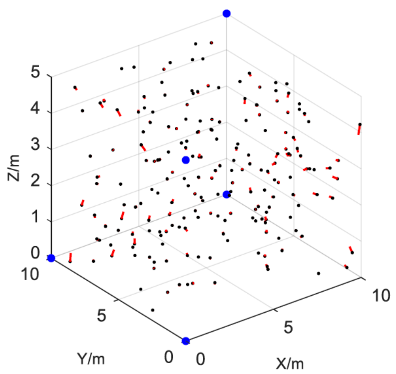
Figure 2 Unknown node positioning accuracy under random deployment, shrink deployment and optimal deployment of five anchor nodes, (a) random deployment (b) shrink deployment (c) optimal deployment (see online version for colours)



(a)



(b)



(c)

Notes: Blue solid dots represent anchor nodes, black solid dots represent unknown nodes, and red lines represent ranging error.

Figure 3 shows the degree of influence of ranging noise on the positioning performance of different deployment schemes of anchor nodes when the number of anchor nodes is 8. When the ranging noise variance increases from 0.2^2 to 0.6^2, the positioning errors for random deployment, shrink deployment and optimal deployment increase from 0.37 m, 0.34 m, 0.29 m to 1.04 m, 0.97 m, 0.82 m, respectively. Obviously, as the ranging variance increases, the ranging variances of all deployment schemes show an increasing trend. In the case of the same ranging variance, optimal deployment has the smallest positioning error, and the random deployment has the largest positioning error, which is consistent with the results in Figure 1.

Figure 3 The effect of ranging noise on the positioning performance of different deployment schemes of anchor nodes (see online version for colours)

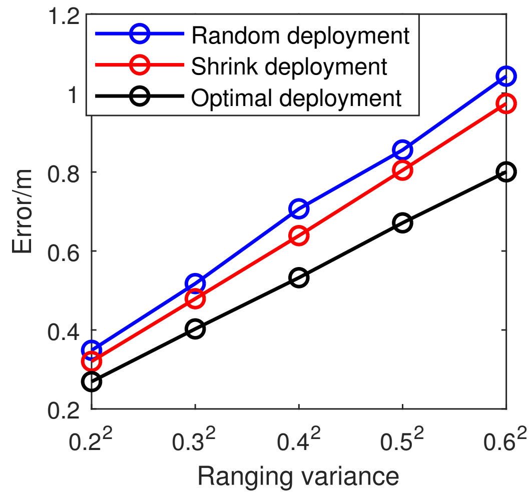


Figure 4 The comparison of the positioning errors of different algorithms when optimally deployed under eight anchor nodes (see online version for colours)

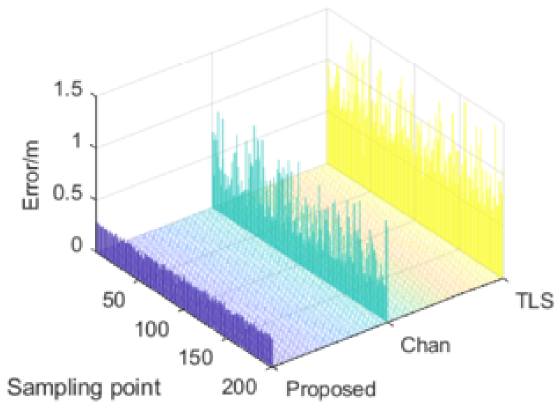


Figure 4 shows the comparison of the positioning errors of different algorithms when optimally deployed under eight anchor nodes. The overall positioning errors of the TLS algorithm, the Chan algorithm and the proposed algorithm are 0.80 m, 0.50 m and 0.29 m respectively, indicating that the overall positioning accuracy of the algorithm proposed in this paper is high. The maximum positioning errors of the TLS algorithm, the Chan algorithm and the proposed algorithm are 1.40 m, 1.05 m and 0.33 m, respectively, and the minimum positioning errors are 0.29 m, 0.22 m and

0.20 m, respectively. The positioning error of the algorithm in this paper varies slightly, and the positioning effect is stable.

Figure 5 The comparison of positioning errors with and without PSO algorithm optimisation under optimal deployment of eight anchor nodes (see online version for colours)

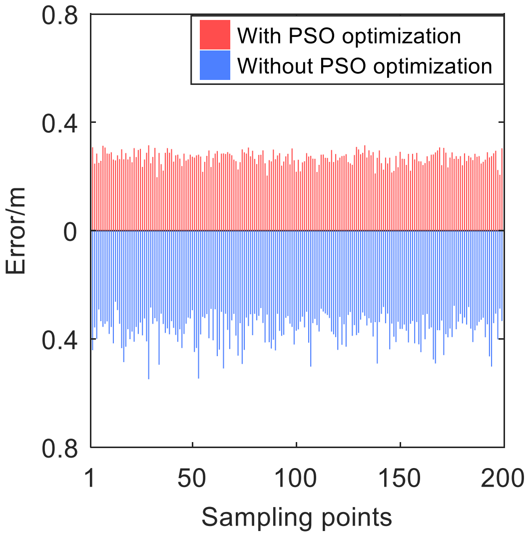


Figure 5 shows the comparison of positioning errors with and without PSO algorithm optimisation under optimal deployment of eight anchor nodes. The positioning error without PSO algorithm optimisation is 0.37 m, and the maximum positioning error is 0.55 m; the positioning error with PSO algorithm optimisation is 0.27 m, and the maximum positioning error is 0.32 m. The positioning accuracy with PSO optimisation is more stable, indicating that the PSO algorithm effectively reduces the influence of other factors such as ill-conditioned matrix on the positioning accuracy. Therefore, intelligent algorithms can be used to improve the accuracy and stability of wireless positioning.

5 Conclusions

This paper mainly deduces optimal deployment of anchor nodes theoretically. First, we deduce the third-order matrix that can characterise the positioning error from the least squares equation, and discuss the upper and lower bounds of the eigenvalues from the perspective of the minimum positioning error. Then, optimal deployment topology of anchor nodes is obtained when the number of anchor nodes is 4, 5, 6, 7 and 8. The simulation results show that: the positioning of optimal deployments with different anchor node numbers is much better than random deployments. Compared with the shrink deployment, the performance of optimal deployment is improved by 20.6%; when the ranging noise variance increases from 0.2^2 to 0.6^2, the positioning errors for random deployment, shrink deployment and optimal deployment increase from 0.37 m, 0.34 m and 0.29 m to 1.04 m, 0.97 m and 0.82 m, respectively. With the increase of ranging noise, the positioning errors of different deployment schemes all show an increasing trend. The positioning algorithm proposed in this paper is compared with the other algorithms, which shows the superiority and stability of the proposed algorithm in this paper.

On the one hand, these simulation results show that the optimal deployment of anchor nodes can effectively improve the overall accuracy of wireless positioning, which is of great significance for improving the accuracy of wireless positioning by deploying anchor nodes in advance. On the other hand, it shows that the intelligent search algorithm can effectively improve the stability of wireless positioning and reduce the influence of ill-conditioned matrix on wireless positioning results. It is of great significance to use the intelligent search algorithm to improve the positioning accuracy of the distributed solution.

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