附件1-14 论文14 本项目成员关伟鹏、蔡烨、谢灿宇为论文作者

Optical Engineering

OpticalEngineering.SPIEDigitalLibrary.org

Three-dimensional high-precision indoor positioning strategy using Tabu search based on visible light communication

Qi Peng
Weipeng Guan
Yuxiang Wu
Ye Cai
Canyu Xie
Pengfei Wang

SPIE.

Qi Peng, Weipeng Guan, Yuxiang Wu, Ye Cai, Canyu Xie, Pengfei Wang, "Three-dimensional high-precision indoor positioning strategy using Tabu search based on visible light communication," *Opt. Eng.* **57**(1), 016101 (2018), doi: 10.1117/1.OE.57.1.016101.

Optical Engineering 57(1), 016101 (January 2018)

Three-dimensional high-precision indoor positioning strategy using Tabu search based on visible light communication

Qi Peng,[a] Weipeng Guan,[b,*] Yuxiang Wu,[b] Ye Cai,[b] Canyu Xie,[a] and Pengfei Wang[a]
[a]South China University of Technology, School of Materials Science and Engineering, Guangzhou, Guangdong, China
[b]South China University of Technology, School of Automation Science and Engineering, Guangzhou, Guangdong, China

Abstract. This paper proposes a three-dimensional (3-D) high-precision indoor positioning strategy using Tabu search based on visible light communication. Tabu search is a powerful global optimization algorithm, and the 3-D indoor positioning can be transformed into an optimal solution problem. Therefore, in the 3-D indoor positioning, the optimal receiver coordinate can be obtained by the Tabu search algorithm. For all we know, this is the first time the Tabu search algorithm is applied to visible light positioning. Each light-emitting diode (LED) in the system broadcasts a unique identity (ID) and transmits the ID information. When the receiver detects optical signals with ID information from different LEDs, using the global optimization of the Tabu search algorithm, the 3-D high-precision indoor positioning can be realized when the fitness value meets certain conditions. Simulation results show that the average positioning error is 0.79 cm, and the maximum error is 5.88 cm. The extended experiment of trajectory tracking also shows that 95.05% positioning errors are below 1.428 cm. It can be concluded from the data that the 3-D indoor positioning based on the Tabu search algorithm achieves the requirements of centimeter level indoor positioning. The algorithm used in indoor positioning is very effective and practical and is superior to other existing methods for visible light indoor positioning. [DOI: 10.1117/1.OE.57.1.016101]

Keywords: visible light communication; three-dimensional indoor positioning; Tabu search; positioning accuracy.

Paper 171661 received Oct. 21, 2017; accepted for publication Dec. 6, 2017; published online Jan. 2, 2018.

1 Introduction

Nowadays, with the rapid development of wireless sensor network and physical networking technology, demands for location-based services gradually present a significant growth trend.[1–3] In the field of positioning, global positioning system (GPS) is well known for its wide coverage and low cost of application. GPS has found an increasingly wide utilization in many situations, such as vehicle navigation, map service, and so on. For outdoor environment, GPS has provided satisfactory services; however, it has low accuracy in indoor positioning.[4] GPS is still far from a perfect system in the field of positioning when it comes to a situation that indoor environment for radio signals from a satellite will be blocked by tall buildings, causing big positioning error. To meet the increasing need of indoor positioning service, wi-fi, bluetooth, radio frequency identification (RFID), and camera-based positioning systems have been developed to complement GPS. All positioning systems mentioned above can provide a position precision from tens of centimeters to several meters and some of them have already been used in indoor environment. However, due to the disadvantages of high cost, low positioning accuracy, electromagnetic interference, and other factors, the schemes above are not ideal candidates.[5] Those solutions of indoor positioning have the following disadvantages: (1) to install these systems, extra device should be added to an indoor environment, which increases the cost and complexity of operation and control. (2) In some RF-inappropriate environments, such as an underground mine, radio-based indoor positioning systems do not work at all. (3) The uneven spatial distribution of wireless signal leads to an intense volatility at a same location, which results in a reduction of positioning accuracy. (4) These radio-based positioning systems will produce the electromagnetic interference to the indoor electronic device such as an MRI scanner in a hospital, so some particular places cannot allow these systems to work. (5) The confidentiality of radio-based communication system is usually not high, which may lead to a location information leakage.

Visible light communication (VLC)-based positioning is a new solution of indoor positioning, which has the advantages of high positioning, no electromagnetic interference, fewer extra modules, good communication confidentiality, and realization of integration of lighting and communication. Positioning systems based on VLC can be divided into many formats: (1) photodiode-based (PD-based), (2) image sensor-based,[6,7] and (3) solar cell-based.[8] As an image sensor-based positioning system usually needs to use an image processing technique, which sets a great demand on system performance and solar cell based is not often used, the simplicity, reliability, and low cost of a PD-based positioning system show wide application in indoor positioning field. For example, Hsu et al.[9] demonstrated a 3×3 imaging MIMO VLC system using white light-emitting diodes (LEDs) and low-cost PIN PDs, which can achieve 1 Gbps data rate over 1-m free-space transmission distance. In PD-based systems, the receiver collects optical signal from signal sources to

*Address all correspondence to: Weipeng Guan, E-mail: gwpscut@163.com

0091-3286/2018/$25.00 © 2018 SPIE

estimate the distance between itself and the signal sources using a series of methods of received signal strength (RSS),[10,11] angle of arrival (AOA),[12] time of arrival (TOA),[13] time difference of arrival (TDOA),[14,15] and so on. Among these methods introduced, TOA and TDOA are immune to noise, and the AOA measures the distance by the angle of received signal, whereas this is difficult to achieve in reality for the layout of transmitters, and the receiving range of a PD brings a dramatic effect on the AOA measured, which results in a big error in positioning accuracy. Instead, the RSS detects the distance only according to the RSS, which can reduce the complexity of the circuit of transmitters while ensuring the localization accuracy of the premise. At the same time, for a receiver, it is easy to measure the signal strength using an AD converter. Hence, RSS is studied deeply. For example, Yang et al.,[16] proposed an indoor positioning system using single transmitter and multiple receivers, the device can find its location using RSS and the relative position of optical receivers, the average positioning error was reported to be 0.65 cm. Jung et al.[17] defined received signal strength ratio (RSSR) between received signals, three equations could be obtained using the distance ratios, which is a function of RSSR, the target can be located by solving the equations. The methods above both achieve satisfied precision; however, they fail to give the height information.

Three-dimensional indoor positioning has been done by some predecessors. For example, Hou et al.[18] used only an LED lamp with RSS and AOA algorithm to achieve 3-D positioning, and its positioning error is 10.2 cm. In this article, the positioning accuracy is high, but the hybrid algorithm is used for positioning, which is complex in calculation. Yasir et al.[19] used the light sensor and accelerometer of the smart phone to measure the light intensity and locate the smart phone combined with the low complexity algorithm, and the error <25 cm is achieved. This method needs to add some additional devices, which increases the cost. Lim[20] proposed a maximum likelihood approach for the positioning system and enhanced the positioning performance by employing an iterative maximum likelihood approach by adopting the least square solution as an initial guess, and the accuracy is not high. Wu et al.[21] built a simplified 3-D fingerprint database in the condition of linear light-intensity attenuation model and combined fingerprint database method with the iterative algorithm to achieve 3-D positioning whose error is 4.1 cm in X–Y plane, and the z direction error is 5.4 cm. The method achieves satisfied precision, but this method needs to build a fingerprint database first. So far, the results of 3-D positioning are not satisfactory.

To actualize the indoor positioning using visible light, the problem that should be solved first is the interference of optical communication. The introduction of a multiple access technique is necessary. In consideration of the possibility of many LEDs existing in an indoor environment at the same time, the frequency bands will be divided into different sub channels which have different bandwidth when using the frequency division multiple access resulting in the difficulty of filter design. As for the time division multiple access, it will be difficult to control the transmitters for the communication time slot, which will be short when there are too many LEDs. The code-division multiple access (CDMA) modulation can separate the signal overlapping both in time domain and frequency domain, and the spread spectrum technology in CDMA can also reduce the intersymbol interference caused by the presence of multipath effect indoor. Therefore, CDMA can improve communication quality and increase system stability. In this article, CDMA is used to modulate ID information, which is transmitted from different LEDs. The CDMA technique is not described in detail in this article, if readers are interested in CDMA technique, you can refer to our previous article.[22–24]

In view of the fact that the existing 3-D indoor positioning is not effective, we propose a 3-D high-precision indoor positioning strategy using Tabu search[25,26] for 3-D visible light indoor positioning. Tabu search is a powerful global optimization algorithm, and the 3-D indoor positioning can be transformed into an optimal solution problem. Therefore, in the 3-D indoor positioning, the optimal receiver coordinate can be obtained by the Tabu search algorithm and this is the first time the Tabu search algorithm is applied to visible light positioning. The algorithm restricts the search process falling into local optimization using Tabu strategy to avoid roundabout search. And the algorithm adds amnesty criterion to get the appropriate positioning coordinate, so the amnesty criterion ensures the effectiveness and diversity of the process in searching for optimal positioning coordinate. When the fitness value satisfies the condition, the optimal coordinate is obtained. Compared with existing 3-D positioning system, it has higher accuracy and does not need additional devices. The results show that while using the Tabu search algorithm for 3-D indoor positioning, the maximum error is 5.88 cm and the mean error is 0.79 cm.

The rest of this article is arranged as follows: Sec. 2 introduces the system model of indoor visible light positioning, proposes the Tabu search algorithm, and shows how to use the Tabu search algorithm for 3-D indoor positioning. Section 3 shows the simulation and experimental results. Section 4 draws the conclusion of this article.

2 System Principle and Positioning Algorithm

2.1 *Indoor Wireless Optical Channel*

The indoor visible light positioning model is shown in Fig. 1. Four LEDs are installed at the ceiling of the room, and the receiver is located at a certain height of the room. Each LED sends localized ID information, which is modulated in CDMA, and the receiver converts the optical signal into a certain size electric signal according to the conversion efficiency of photoelectric detector (PD). In this article, LED is a Lambertian light source, so line-of-sight channel gain of this visible light indoor positioning system can be given by[27]

$$H(0)_{\mathrm{LOS}}=\begin{cases}\frac{(m+1)A_r}{2\pi d^2}\cos^m(\theta)\cos(\psi)T_s(\psi)G(\psi), & 0\leq\psi\leq\mathrm{FOV}\\ 0, & \psi\geq\mathrm{FOV}\end{cases}, \tag{1}$$

where A_r is the effective area of the PD. d is the distance between the LED and the receiver. θ is the irradiant angle relative to the vertical axis of the LED. ψ is the incident angle relative to the receiving axis. $T_s(\psi)$ is the gain of optical filter, and $G(\psi)$ is the gain of optical concentrator. FOV is the field of view of the receiver. m indicates the order of Lambert's luminous intensity, which can be given by the following equation:[28]

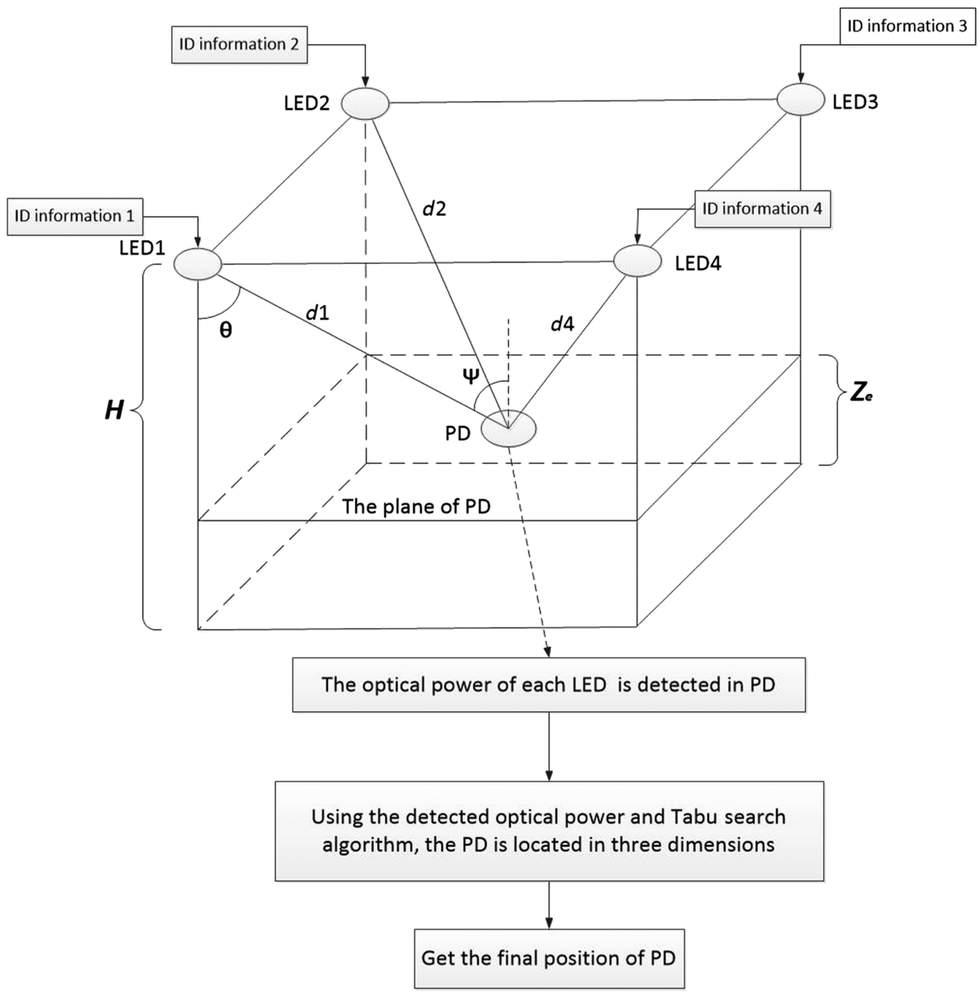

Fig. 1 Indoor visible light positioning system.

$$m = -\frac{\ln 2}{\ln[\cos(\theta_{1/2})]}, \tag{2}$$

where $\theta_{1/2}$ is the half-power angle of the transmitter (LED).

The following discussion is about $0 \le \psi \le \text{FOV}$. The received optical power P_r can be represented as

$$P_r = H(0)_{\text{LOS}} \cdot P_t$$
$$= \frac{(m+1)A_r}{2\pi d^2}\cos^m(\theta)\cos(\psi)T_s(\psi)G(\psi)P_t, \tag{3}$$

where P_t is the average transmitted optical power.

In the room model, the coordinate of LED is (x_t, y_t, and z_t, and the coordinate of receiver coordinate is x_r, y_r, z_r). Thus, the irradiant angle θ can be represented as[29]

$$\cos(\theta) = \frac{z_t - z_r}{[(x_t - x_r)^2 + (y_t - y_r)^2 + (z_t - z_r)^2]^{\frac{1}{2}}}. \tag{4}$$

Since it is assumed that the plane at which the receiver is located is parallel to the ceiling, the incident angle ψ is equal to the irradiant angle θ. $\cos(\psi) = \cos(\theta)$. Equation (3) can be expressed as the following equation:

$$P_r = \frac{(m+1)A_r}{2\pi}T_s(\psi)G(\psi)$$
$$\times \frac{(z_t - z_r)^{m+1}}{[(x_t - x_r)^2 + (y_t - y_r)^2 + (z_t - z_r)^2]^{\frac{m+3}{2}}}P_t. \tag{5}$$

We can also simplify Eq. (5) to

$$P_r = R\frac{(z_t - z_r)^{m+1}}{[(x_t - x_r)^2 + (y_t - y_r)^2 + (z_t - z_r)^2]^{\frac{m+3}{2}}}P_t, \tag{6}$$

where

$$R = \frac{(m+1)A_r}{2\pi}T_s(\psi)G(\psi), \tag{7}$$

R is a constant obtained in the VLC-positioning system. The distance between the LED and the receiver d can be expressed as

$$d = [(x_t - x_r)^2 + (y_t - y_r)^2 + (z_t - z_r)^2]^{\frac{1}{2}}, \tag{8}$$

d can eventually be represented as

$$d = \left[\frac{R(z_t - z_r)^{m+1} P_t}{P_r}\right]^{\frac{1}{m+3}}. \tag{9}$$

In the VLC system, the total variance of the system channel noise σ^2_{noise} obeys the Gauss distribution, which is the sum of shot noise and thermal noise[30]

$$\sigma^2_{\text{noise}} = \sigma^2_{\text{shot}} + \sigma^2_{\text{thermal}}, \tag{10}$$

σ^2_{shot} is caused by the optical power including the effective signal strength and the lighting environment, and $\sigma^2_{\text{thermal}}$ is caused by random motion of electrons. The signal-to-noise ratio of the VLC positioning system can be expressed as

$$\text{SNR} = 10 \log_{10}\left(\frac{P_r}{\sigma^2_{\text{noise}}}\right). \tag{11}$$

2.2 *Three-Dimensional Positioning Algorithm Based on Tabu Search*

First of all, we are going to introduce the Tabu search algorithm. Its essence is to search the solution space according to a certain rule until it searches for the approximate optimal solution or the optimal solution, and it belongs to the global optimization algorithm. In the application of 3-D indoor positioning, the solution space is positioning coordinates, which is in the room. During the search process, one solution produces a certain number of neighbor solutions according to a specific equation. Candidate solution is the best solution selected from neighbor solutions according to fitness value. The Tabu list is a container used to store the taboo object. The taboo object is an element placed in the Tabu list, and the element is the positioning coordinates in the application of 3-D indoor positioning. The taboo object in Tabu list cannot be searched again until the taboo is lifted. The Tabu list simulates human memory mechanism, so it prevents search from being trapped into local optimization to explore more search space. The taboo length is the maximum number of taboo objects stored in the Tabu list. When the number of taboo objects exceeds the taboo length, the taboo object, which got into Tabu list first should be removed before storing a new taboo object. The amnesty criterion is that the positioning coordinate of the receiver is output directly when the fitness value satisfies certain condition.

Four LEDs installed at the ceiling of the room send localized ID information. Different ID information modulated in CDMA technology and then is received by PD. When the received optical power is detected by PD, the best positioning coordinate can be obtained using the Tabu search algorithm.

Step 1. Initializing the current estimated location $x_{\text{now}} = (x_e, y_e, z_e) = (0, 0, 0)$, and the current best location $x_{\text{best}} = (x_b, y_b, z_b) = (0,0,0)$. Setting upper bound $x_u = 4$ and lower bound $x_l = 0$, which is used in equation producing a certain number of neighbor locations. Setting taboo length $L = 13$, attenuation factor scale $= 1$, and maximum number of iteration $G_{\max} = 2000$. Emptying the Tabu list. Then go to step 2.

Step 2. From Eq. (9), we learn that the distance between the LED and the receiver can be expressed as

$$d_e^{(i)} = \left[\frac{R(z_t - z_e)^{m+1} P_t}{P_r^{(i)}}\right]^{\frac{1}{m+3}}, \tag{12}$$

where z_t is the height of LED and also the height of the room. $d_e^{(i)}$ is the distance between the receiver and LED (i) $(i = 1,2,3,4)$. $P_r^{(i)}$ is the received optical power detected by PD.

The coordinate of LED(i) is $x_{\text{LED}(i)} = [x^{(i)}, y^{(i)}, z_t], (i = 1,2,3,4)$. The distance between the current estimated location x_{now} and LED(i) can be represented as

$$d^{(i)} = \sqrt{\{[x_e - x^{(i)}]^2 + [y_e - y^{(i)}]^2 + (z_e - z_t)^2\}}. \tag{13}$$

$\Delta(i)$ is defined as

$$\Delta(i) = [d^{(i)} - d_e^{(i)}]^2 \tag{14}$$

So, we get the fitness value

$$\text{fit} = \sum_{i=1}^{i=4} \Delta(i). \tag{15}$$

If fit $< 1 \times 10^{-5}$, then we output the current estimated location x_{now} as the final location coordinate. If fit $\geq 1 \times 10^{-5}$, then go to step 3. At the same time judging if the number of iterations is maximal, and if the number of iterations is maximal, go back to step 1.

Step 3. We know that the current estimated location is $x_{\text{now}} = (x_e, y_e, z_e)$, and we use x_{now} to generate neighbor locations $x_{\text{near}(j)} = [x_n^{(j)}, y_n^{(j)}, z_n^{(j)}]$, $(j = 1,2,3,\ldots,20)$. In this step, it is necessary to update the value of scale

$$\text{scale}_{\text{next}} = \text{scale}_{\text{last}} * 0.998. \tag{16}$$

That is, the next scale value is 0.998 times the scale value in the last iteration loop.

So, we get $x_{\text{near}(j)}$ through this equation

$$\begin{cases} x_n^{(j)} = x_e + \text{rand} * \text{scale} * (xu - xl) \\ y_n^{(j)} = y_e + \text{rand} * \text{scale} * (xu - xl), \\ z_n^{(j)} = z_e + \text{rand} * \text{scale} * (xu - xl) \end{cases} \tag{17}$$

rand is a random value in the range of $[-1,1]$. First, we calculate the fitness value of 20 neighbor locations fit_{near}, then from 20 neighbor locations we select the one with the minimum fit_{near} as the candidate location $x_{\text{candidate}}$. And we calculate the fitness value of the candidate location $\text{fit}_{\text{candidate}}$. Then, go to step 4.

Step 4. First, we calculate the fitness value of the current best location fit_{best}. If $\text{fit}_{\text{candidate}} < \text{fit}_{\text{best}}$, then we make $x_{\text{best}} = x_{\text{candidate}}, x_{\text{now}} = x_{\text{candidate}}$, and add the candidate location $x_{\text{candidate}}$ into Tabu list. If the number of taboo objects exceeds the taboo length, remove the taboo object, which got into Tabu list first, and then go back to step 2. If $\mathrm{fit}_{\mathrm{candidate}} \geq \mathrm{fit}_{\mathrm{best}}$, then go to step 5.

Step 5. First, we judge whether the candidate location is in Tabu list. If the candidate location is in the Tabu list, the current estimated location x_{now} remains unchanged, and then go back to step 2. If the candidate location is not in the Tabu list, make $x_{\mathrm{now}} = x_{\mathrm{candidate}}$, and add the candidate location $x_{\mathrm{candidate}}$ into Tabu list. If the number of taboo objects exceeds the taboo length, remove the taboo object, which got into Tabu list first, and then go back to step 2.

The framework of the proposed the Tabu search algorithm for 3-D positioning is shown in Fig. 2.

3 Simulation and Analysis

3.1 *Design of Indoor Three-Dimensional Positioning Simulation Model*

Software simulation is used to test the performance of the Tabu search algorithm in 3-D positioning. There are four LEDs located on the ceiling of room with a size of $3\ \mathrm{m} \times 3\ \mathrm{m} \times 4\ \mathrm{m}$, and the PD located at an unknown position. The coordinate of each LED is LED1 (0, 0, 4), LED2 (3, 0, 4), LED3 (3, 3, 4), and LED4 (0, 3, 4), respectively. Other simulation setup parameters of the positioning system are listed as follows: the LED power is 5 W; the FOV of PD is 90 deg; the effective area of PD is $1\ \mathrm{cm}^2$; the gain of optical filter is 1; the gain of optical concentrator is 1; the half-power angle of LED is 60 deg; the order of Lambert's luminous intensity is 1. And the parameters of the Tabu search algorithm will be presented in the Table 1. Each of these four LED bulbs will transmit localized ID information. Different ID information is modulated in CDMA to spread spectrum and then is received by PD whose estimated position can be calculated by the Tabu search algorithm. The parameters used for the 3-D indoor positioning system are shown in Table 1.

3.2 *Result and Discussions*

To estimate the performance of the Tabu search algorithm in 3-D indoor positioning, in this section, a multipoint positioning test is adopted and the positioning is performed at different heights. As shown in Fig. 3, the resolution of the real tested position point is 0.5 m, so there are 25 real tested position points in every plane, which are represented by "×." And the position point calculated by Tabu search is represented by

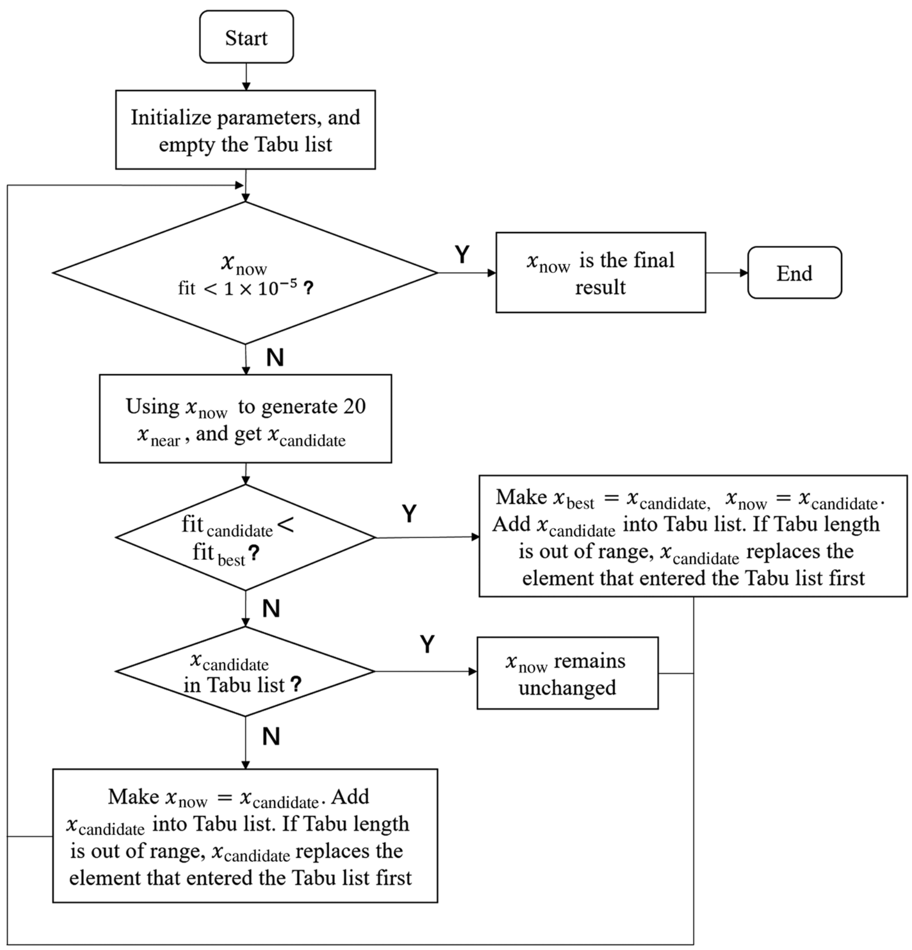

Fig. 2 Framework of the Tabu search algorithm for 3-D positioning.

Table 1 Parameters of the 3-D positioning system.

Parameter	Value
Room size $(L \times W \times H)/m$	3 m × 3 m × 4 m
Position of each LED $(x, y, z)/m$	LED1 (0, 0, 4)
	LED2 (3, 0, 4)
	LED3 (3, 3, 4)
	LED4 (0, 3, 4)
LED power $[P_t]/W$	5
The FOV of PD/deg	90
The effective area of PD $[A_r]/cm^2$	1
The gain of optical filter $[T_s(\psi)]$	1
The gain of optical concentrator $[G(\psi)]$	1
The half-power angle of LED $[\theta_{1/2}]/$ deg	60
The order of Lambert's luminous intensity $[m]$	1
Upper bound $[x_u]$	4
Low bound $[x_l]$	0
Tabu length $[L]$	13
Maximum number of iteration $[G_{max}]$	2000
The initial value of the attenuation factor [scale]	1
Number of neighbor locations $[x_{near}]$	20

"Δ". In this test, positioning tests are performed at 10 different heights of the plane. The height was set to 0.2, 0.4, 0.6, 0.8, 1, 1.2, 1.4, 1.6, 1.8, and 2 m, respectively, as shown in Figs. 3(a)–3(f).

The result shows that the 3-D positioning is good, and the real position is very close to the position estimated by the Tabu search algorithm. To assess the performance of a positioning system more accurately and directly, we conduct further quantitative analysis.

The positioning error is defined as the linear distance between the real position and the estimated position. When the positioning error is calculated, the 3-D error map of different height is obtained, as shown in Fig. 4. The abscissa axis of Fig. 5 shows the height of Z-axis, and the vertical axis represents the average error between 25 tested point and its estimated point in different heights.

As we can see from Fig. 4, when the height is 0.2 m, the maximum error is 0.96 cm and the average error is 0.60 cm; when the height is 0.4 m, the maximum error is 1.20 cm and the average error is 0.55 cm; when the height is 0.6 m, the maximum error is 0.87 cm and the average error is 0.52 cm; when the height is 0.8 m, the maximum error is 0.88 cm and the average error is 0.55 cm; when the height is 1 m, the maximum error is 1.28 cm and the average error is 0.55 cm; when the height is 1.2 m, the maximum error is 1.45 cm and the average error is 0.62 cm; when the height is 1.4 m, the maximum error is 1.79 cm and the average error is 0.81 cm; when the height is 1.6 m, the maximum error is 1.53 cm and the average error is 0.74 cm; when the height is 1.8 m, the maximum error is 3.18 cm and the average error is 1.17 cm; when the height is 2 m, the maximum error is 5.88 cm and the average error is 1.83 cm; by analyzing the above data we can know when the height is low, the error of different heights is basically the same; when the height rises to a certain height, the error significantly increased with an increase in the height. It is because when the height is high, the irradiant angle θ of LED and the incident angle ψ of PD will increase, and when they increase to a certain extent, the luminous intensity of LED is weakened, and the optical power received by PD will be reduced, which leads to the increase in the error of the received optical power. Therefore, when the height is high, the 3-D error will increase significantly. Figure 5 is the line chart for the average error between 25 tested points and its estimated point in different heights. It can be seen that the error will increase significantly when the height is higher.

Figure 6 is the histogram of error between 250 tested positioning points and its TS estimated positioning point in multipoint positioning test. The maximum error is 5.88 cm, and the average error is 0.79 cm, and most of the positioning errors are below 1 cm. Figure 7. is the cumulative distribution function (CDF) curves of position errors. From Fig. 7, we can see that 95.2% positioning errors are below 1.791cm. The results show that the effect of the Tabu search algorithm for 3-D positioning is good, the average error can reach mm level.

3.3 *Extended Simulation and Result Analysis*

To evaluate the performance of the Tabu search algorithm in real-time positioning, an extended simulation experiment of trajectory tracking is carried out. The system parameters of the trajectory tracking simulation are just the same as the parameters shown in Sec. 3.1. First, we generate a random curve. Then, we track the random trajectory with 101 positioning points.

As shown in Fig. 8, the black line represents the random trajectory, and the red "*" represents the positioning tracking of the trajectory. To better display the tracking effect, Figs. 9 and 10 show the results in a horizontal view and vertical view, respectively. We can see that the tracking effect is good.

To directly perform the result of 3-D positioning, the histogram of positioning error and the CDF curves of position error in trajectory tracking are shown in Figs. 11 and 12, respectively. As shown in Fig. 11, most of the positioning errors in trajectory tracking are below 1 cm, and with an increase in the height of the trajectory, the positioning error is larger than 2 cm, which is consistent with the analysis in Sec. 3.2. From Fig. 12, we can see that 95.05% positioning errors in trajectory tracking are below 1.428 cm. It can be concluded from the above results that using the Tabu search algorithm for trajectory tracking effect is good and further proved that the Tabu search algorithm for indoor 3-D positioning is good.

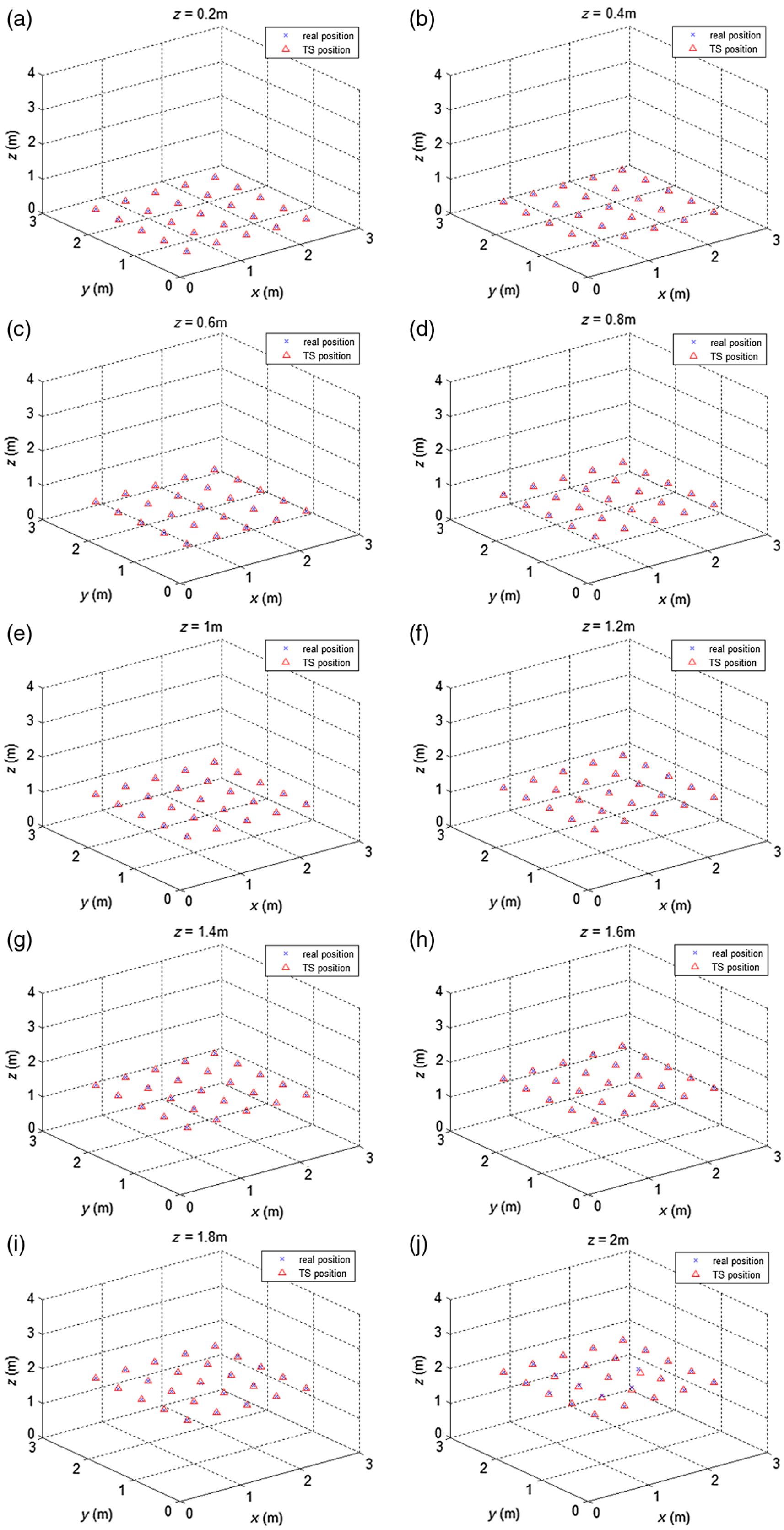

Fig. 3 Distribution of the real position point and its TS estimated position point: (a)–(j) is the positioning result of 0.2, 0.4, 0.6, 0.8, 1, 1.2, 1.4, 1.6, 1.8, and 2 m, respectively.

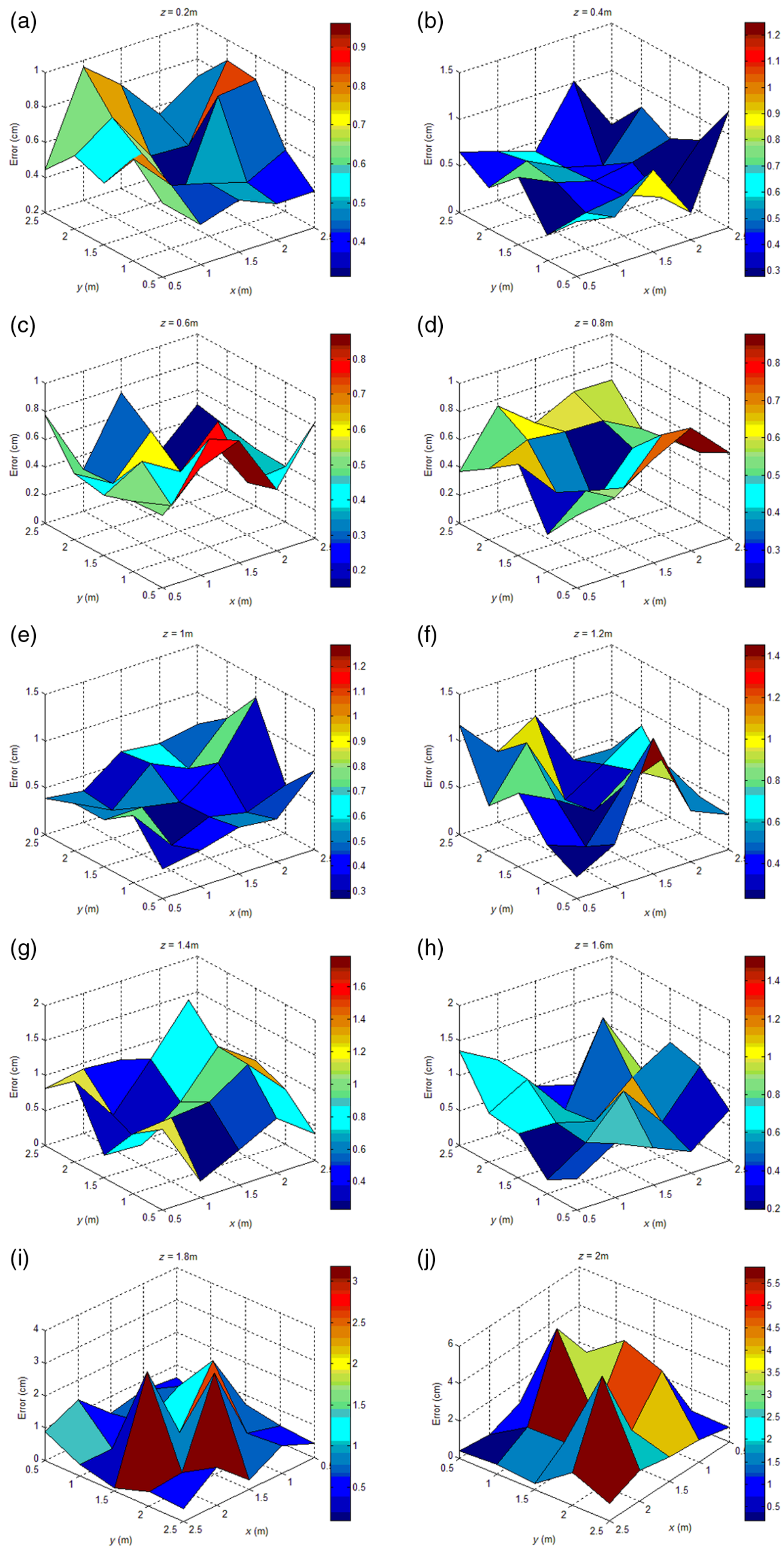

Fig. 4 Three-dimensional error of different heights: (a)–(j) is the 3-D error of 0.2, 0.4, 0.6, 0.8, 1, 1.2, 1.4, 1.6, 1.8, and 2 m, respectively.

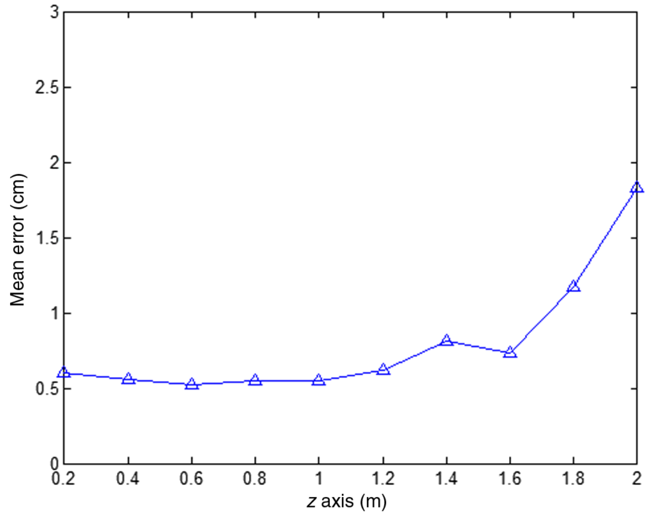

Fig. 5 Mean error of different heights.

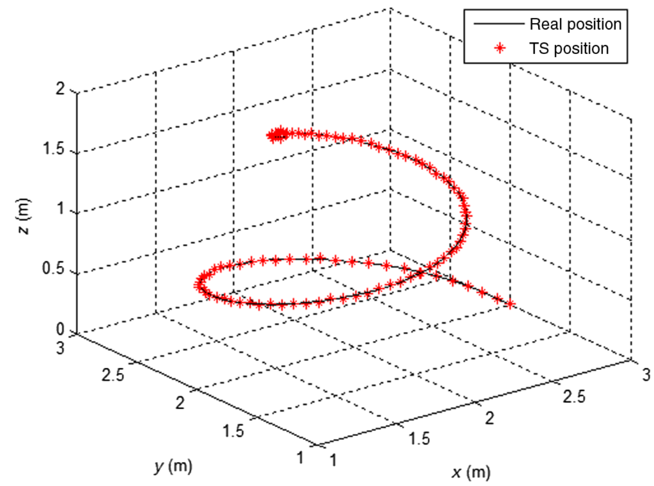

Fig. 8 3-D position in trajectory tracking.

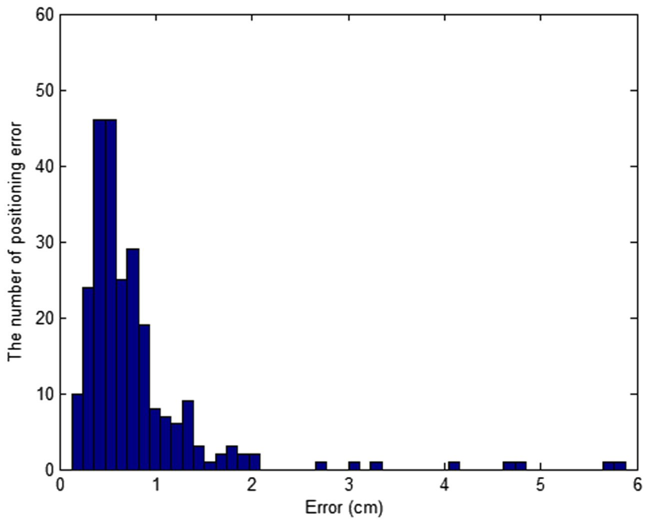

Fig. 6 Histogram of position errors.

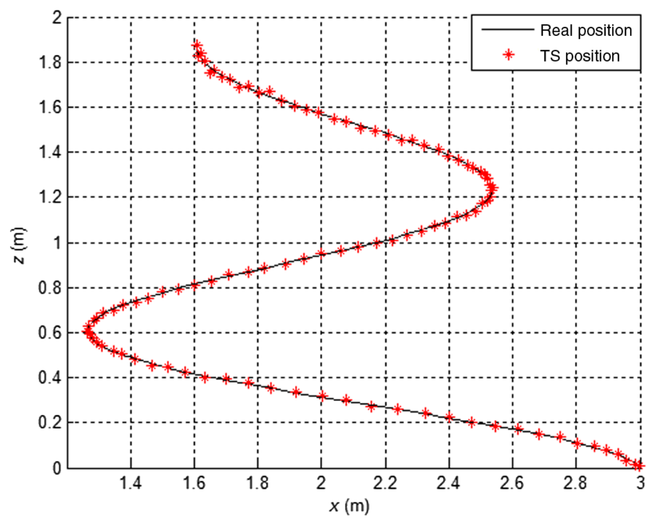

Fig. 9 The horizontal positioning result of trajectory tracking.

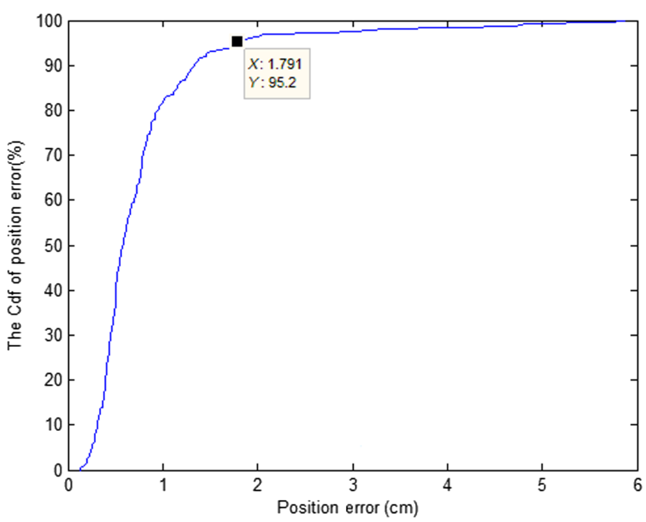

Fig. 7 The CDF curves of position errors.

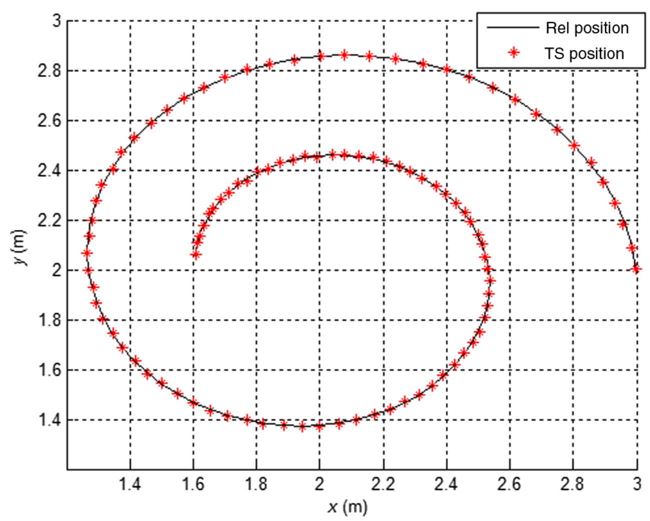

Fig. 10 The vertical positioning result of trajectory tracking.

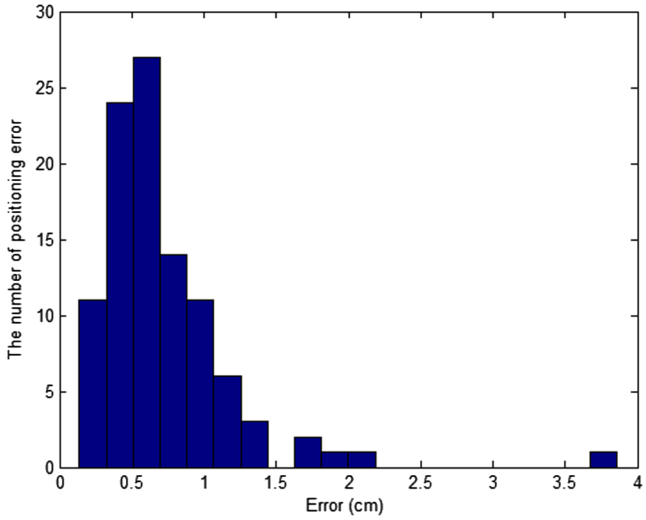

Fig. 11 Histogram of position error in trajectory tracking.

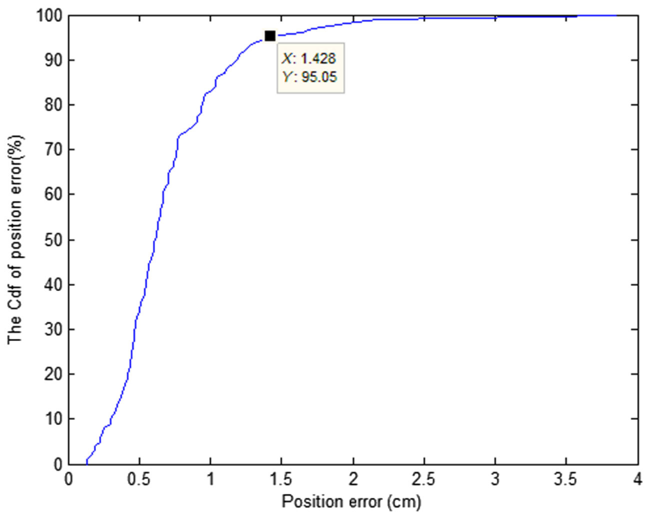

Fig. 12 The CDF curves of position error in trajectory tracking.

4 Conclusion

In this work, a 3-D high-precision indoor positioning strategy using Tabu search is proposed. With the advantage of the global optimization of the Tabu search algorithm, high-precision 3-D indoor positioning can be achieved. It is the first time that the Tabu search algorithm is applied to visible light positioning, which is innovative. Each LED sends localized ID information, and when the receiver PD detects optical signals with ID information from different LEDs, the Tabu search algorithm is used to locate the PD. The experiment results show that the positioning effect is good, which is superior to the existing indoor 3-D positioning.

In the dimension of $3 \text{ m} \times 3 \text{ m} \times 4 \text{ m}$, static multipoint positioning test was carried out first. The data show that the maximum error is 5.88 cm, and the average error is 0.79 cm in 250 tested positioning points. Most of the positioning errors are <1 cm. Among them, 95.2% of the positioning errors are below 1.791 cm. Then, the dynamic trajectory tracking was done next. The data show that the vast majority of the positioning errors are <1 cm, and 95.05% of the positioning errors are below 1.428 cm. Both static multipoint positioning test and dynamic trajectory tracking experiment show that the Tabu search algorithm has a good effect in 3-D positioning. The 3-D indoor positioning based on the Tabu search algorithm has potential application value in various indoor positioning scenes.

Acknowledgments

This work was supported by the National Undergraduate Innovative and Entrepreneurial Training Program (Nos. 201510561003, 201610561065, 201610561068, 201710561006, 201710561054, 201710561057, 201710561058, 201710561199, and 201710561202), the Special Funds for the Cultivation of Guangdong College Students' Scientific and Technological Innovation ("Climbing Program" Special Funds) (pdjh2017b0040). We thank the laboratory of Prof. Wu Yuxiang for the use of their equipment.

References

1. M. Yasir, S. W. Ho, and B. N. Vellambi, "Indoor positioning system using visible light and accelerometer," *J. Lightwave Technol.* **32**(19), 3306–3316 (2014).
2. W.-Z. Zhang, M. S. Chowdhury, and M. Kavenhrad, "Asynchronous indoor positioning system based on visible light communications," *Opt. Eng.* **53**(4), 045105 (2014).
3. S. Roehr et al., "Wireless local positioning -existing solutions and novel system concepts," in *IEEE MTT-S Int. Conf. on Microwaves for Intelligent Mobility (ICMIM 2015)* (2015).
4. H. Liu et al., "Survey of wireless indoor positioning techniques and systems," *IEEE Trans. Syst., Man, Cybern. C* **37**(6), 1067–1080 (2007).
5. Y. Cai et al., "Indoor high precision three-dimensional positioning system based on visible light communication using particle swarm optimization," *IEEE Photonics J.* **9**(6), 7908120 (2017).
6. Y. H. Choi et al., "Novel LBS technique based on visible light communications," in *IEEE Int. Conf. on Consumer Electronics*, pp. 576–577 (2012).
7. W. Zhang and M. Kavehrad, "Comparison of VLC-based indoor positioning techniques," *Proc. SPIE* **8645**, 86450M (2013).
8. C.-W. Hsu et al., "Visible light positioning and lighting based on identity positioning and RF carrier allocation technique using a solar cell receiver," *IEEE Photonics J.* **8**(4), 7905507 (2016).
9. C.-W. Hsu et al., "High speed imaging 3×3 MIMO phosphor white-light LED based visible light communication system," *IEEE Photonics J.* **8**(6), 1–6 (2016).
10. W. D. Wang and Q. X. Zhu, "RSS-based Monte Carlo localisation for mobile sensor networks," *IET Commun.* **2**(5), 673–681 (2008).
11. Y. Y. Won et al., "Three-dimensional optical wireless indoor positioning system using location code map based on power distribution of visible light emitting diode," *IET Optoelectron.* **7**(3), 77–83 (2013).
12. M. Dakkak et al., "Indoor localization method based on RTT and AOA using coordinates clustering," *Comput. Networks Int. J. Comput. Telecommun. Networking* **55**(8), 1794–1803 (2011).
13. A. Shi et al., "Impact of multipath effects on theoretical accuracy of TOA-based indoor VLC positioning system," *Photonics Res.* **3**(6), 296 (2015).
14. C. D. Wann, Y. J. Yeh, and C. S. Hsueh, "Hybrid TDOA/AOA indoor positioning and tracking using extended Kalman filters," in *IEEE 63rd Vehicular Technology Conf. VTC 2006-Spring*, pp. 1058–1062 (2006).
15. W. Zhang et al., "Asynchronous indoor positioning system based on visible light communications," *Opt. Eng.* **53**(4), 045105 (2014).
16. S. H. Yang, E. M. Jung, and S. K. Han, "Indoor location estimation based on LED visible light communication using multiple optical receivers," *IEEE Commun. Lett.* **17**(9), 1834–1837 (2013).
17. S. Y. Jung et al., "Received signal strength ratio based optical wireless indoor localization using light emitting diodes for illumination," in *IEEE Int. Conf. on Consumer Electronics (ICCE 2013)*, pp. 63–64 (2013).
18. Y. Hou et al., "A RSS/AOA based indoor positioning system with a single LED lamp," in *Int. Conf. on Wireless Communications and Signal Processing (WCSP 2015)* (2015).
19. M. Yasir, S.-W. Ho, and B. N. Vellambi, "Indoor positioning system using visible light and accelerometer," *J. Lightwave Technol.* **32**(19), 3306–3316 (2014).
20. J. Lim, "Ubiquitous 3D positioning systems by led-based visible light communications," *IEEE Wireless Commun.* **22**(2), 80–85 (2015).
21. D. Wu, L. Feng, and A. Yang, "VLC indoor positioning system based on iterative algorithm," *Proc. SPIE* **9619**, 96190E (2015).

22. W. Guan et al., "A novel three-dimensional indoor positioning algorithm design based on visible light communication," *Opt. Commun.* **392**, 282–293 (2017).
23. W. Guan et al., "High precision three-dimensional iterative indoor localization algorithm using code division multiple access modulation based on visible light communication," *Opt. Eng.* **55**(10), 106105 (2016).
24. W. Guan et al., "Indoor positioning technology of visible light communication based on CDMA modulation," *Acta Opt. Sin.* **36**(11), 1–9 (2016).
25. Y. W. Zhong et al., "The study of neighborhood structure of Tabu search algorithm for traveling salesman problem," in *Proc. 4th Int. Conf. on Natural Computation (ICNC 2008)*, Vol. **1**, pp. 491–495 (2008).
26. S. Khamsawang, C. Boonseng, and S. Pothiya, "Solving the economic dispatch problem with Tabu search algorithm," in *Proc. of the IEEE Int. Conf. on Industrial Technology*, Vol. **1**, pp. 274–278 (2002).
27. W. Guan et al., "High-precision approach to localization scheme of visible light communication based on artificial neural networks and modified genetic algorithms," *Opt. Eng.* **57**(10), 106103 (2017).
28. N. A. Mohammed and M. A. Elkarim, "Exploring the effect of diffuse reflection on indoor localization systems based on RSSI-VLC," *Opt. Express* **23**(16), 20297–20312 (2015).
29. M. T. Niaz et al., "Deployment methods of visible light communication lights for energy efficient buildings," *Opt. Eng.* **55**(10), 106113 (2016).
30. W.-P. Guan et al., "Research on visible light communication system based on hybrid modulation technique," *J. Optoelectron. Laser* **26**(11), 2125–2132 (2015).

Qi Peng is studying for his BE degree in optoelectronic information science and engineering (optoelectronic devices) at the South China University of Technology. Currently, his research is focused on visible light communication and the simulation of indoor positioning system.

Weipeng Guan received his BE degree in electronic science and technology (electronic materials and components) from South China University of Technology, Guangzhou, China, in 2016. He is now working toward his ME degree in control theory and control engineering from the South China University of Technology. His research is currently focused on visible light wireless communication technology and visible light positioning technology.

Yuxiang Wu received her BE degree from the University of Science and Technology Beijing, China, in 1988 and her ME and PhD degrees from the South China University of Technology, Guangzhou, China, in 1994 and 2006, respectively. Currently, she is a professor at the School of Automation, South China University of Technology. She has authored and coauthored many papers in international journals, conferences, and domestic journals. Her current research interests include intelligent control, deterministic learning theory, dynamical pattern recognition, visible light wireless communication technology, and fault diagnosis.

Ye Cai is now studying for her BE degree automation science and engineering at the South China University of Technology. Currently, her research interests concentrate on the area of visible light wireless communication technology and indoor positioning technology.

Canyu Xie is studying for his BE degree in electronic science and technology (electronic materials and components) at the South China University of Technology, Guangzhou, China. Currently, his research is currently focused on visible light communication and the simulation of signal.

Pengfei Wang is studying for his BE degree in electronic science and technology (electronic materials and components) at the South China University of Technology, Guangzhou, China. Currently, his research is focused on visible light communication.