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Visible light positioning system based on CMOS image sensor using particle filter tracking and detecting algorithm

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ABSTRACT

Positioning accuracy, robustness and real-time ability are the three critical elements in visible light positioning (VLP) system. While only a few exiting studies take these three critical elements into consideration at the same time to judge a practical VLP system, causing positioning and tracking method cannot be applied into real situation with different interferences. Therefore, to further improve the three aspects in the round and make it more feasible, a novel VLP method based on image sensor using particle filter tracking algorithm is proposed in this paper. The proposed positioning method locates the position of the terminal equipment with the proportional relationship of world coordinate, image coordinate and camera coordinate. The particle filter is utilized for the fast detection of LED in the image to improve the robustness of VLP system, which is not used for positioning What is more, particle filter algorithm uses HSV (hue, saturation, value) color histogram of signal source as features to realize tracking through importance sampling, weight updating, state estimation and resampling. All three components of HSV are considered and various processing steps of particle filter enhance tracking accuracy and robustness simultaneously. Experimental results show that the particle filter can provide an accuracy of 2.95 cm, which are acceptable in practical application scenarios, demonstrating that the LED detection is so accurate that the positioning accuracy of the positioning algorithm is not affected by the tracking algorithm. At the same time, the proposed algorithm maintains good stability when interference occurs and average computational time for each frame is only 0.021 s, which denotes that the computational cost required for particle filter is so small that the positioning algorithm is not affected by the tracking algorithm and can still have good real-time performance. All these data and performance confirm that the proposed tracking detection algorithm possess practical value and can handle background interference and shielding effect in traditional VLP system based on image sensor.

1. Introduction

According to an international survey carried out by Business Week, more than 80 percent of the data maintained by the organizations worldwide is pertaining to location [1]. And as the indoor activities are becoming more frequent and complex, the demand for location-based services (LBS) continues to increase strongly. Therefore, the indoor positioning systems (IPS) are piloted and deployed widely. In the meantime, the requirements of the IPS are becoming higher to meet the changeable need, which includes positioning accuracy, real-time ability and robustness. Nevertheless, the traditional indoor positioning techniques such as Bluetooth [2,3], radio-frequency identification (RFID) [4–7], wireless local area network (WLAN) [8,9], Zigbee and Ultra Wideband (UWB) fail to give a satisfactory performance with the intrinsic drawbacks of themselves. They either require extra devices which often cost a lot of money, thus are not suitable for large-scale application [10], or perform poorly when facing electromagnetic interference and lead to low robustness. Under the given situation, visible light positioning (VLP) is proposed to improve the performance of positioning systems, owing to the characteristics of low cost, eye-safety, immune to electromagnetic interference and ease of integration with indoor illumination system [11].

Indoor positioning system based on VLP can be divided into two formats: (1) photodiode-based (PD-based), (2) image sensor-based (IS-based) [12]. The photodiode-based positioning system has been studied widely. As it has several downsides shown in previous works [13–17] such as high sensitivity to the direction of the light beam, poor performance on dynamic positioning or tracking, and excessive dependence on many parameters which need measuring accurately, the

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image sensor-based positioning system becomes a promising alternative. Due to the capability of separating light source and standing against ambient light much better than a PD, the image sensor does not require any multiplexing mechanisms and is able to provide much more useful information pertaining to the position of LEDs [18].

To date, several studies based on IS-based VLP have been done. However, these studies do not achieve outstanding results in terms of positioning accuracy, real-time ability and robustness, which are the three significant elements in a VLP system. In [19], a VLP system using image sensor and accelerometer sensor is proposed. The image sensors are used to determine the distances to LEDs, then by solving a set of equations, the position of the IS is obtained. While the accelerometer sensor enables the IS to be tilted at any angle. Their final results show that the positioning accuracy is about 10 cm. However, there is still much space to improve the accuracy. Furthermore, besides the fact that the result is based on theoretical simulation in MATLAB, the researchers point out in their paper that their VLP system is not able to perform well in the shadow region or when the targets move quickly, which means that their system cannot handle the problem of shielding effect and blur situation. In [20], four single LEDs and dual PC cameras are exploited for positioning. It uses image sensor with higher resolution of 1280×960 to diminish the positioning error and eventually achieves the accuracy of 8.5 cm. However, the higher resolution results in additional cost and longer latency of the positioning process, which is undesirable to be applied to practice [18]. In [21], a VLP system based on camera with specular reflection cancellation is demonstrated. It reaches a high positioning accuracy of 1.78 cm, however, it is tested in a very tiny space of 30 cm×30 cm×72 cm with fixed measuring points. When it faces a larger and more complex scene, it may fail to reach the same accuracy. Although much more accurate positioning results have been realized in several studies, they ignore the importance of the real-time ability of a VLP system which may cause long waiting time for users to get the information of their location. In essence, it is not helpful to only improve the positioning accuracy without considering the real-time ability of a VLP system. Md. Tanvir Hossan et al. take the real-time ability into account in [22] by using Kalman filter to minimize the time delay for positioning. They use a smartphone to get the LED-IDs from multiple lights and when the smartphone is moving, the pixel area on the IS changes with the relative motion between the phone and each LED light. Then the distance from the phone to that LED is calculated. Their result in terms of the positioning accuracy is kept within 10 cm. The sampling rate and average run time is 1 Hz, 1 s respectively, which is still far from satisfaction, however. Besides, the uncertainty of Kalman filter is restricted to Gaussian distribution, thus Kalman filter is not the optimal filter when solving non-linear or non-gaussian issues. Therefore, the performance of this system will decrease under these situations. In [23], Yohei Nakazawa et al. proposed an LED-tracking and ID-estimation algorithm using LEDs with known IDs to reduce the cost of installing and running transmitters. They tested the system with the receiver moving at a speed of 10 cm/s and it delivered an accuracy of 6.96 cm. Nevertheless, the velocity of the moving receiver is too low to meet the demand of real-time thus this system cannot be applied to real-life scenarios. Moreover, they overlook the importance of robustness which is usually ignored in the studies of VLP system. As the target is in motion, the LED image obtained by IS may be blurred, which makes the system hard to find the center of each LED and estimate the ID of unknown LEDs. In practice, not only the blur of images but also shielding effect can result in great error or even failure of the VLP system. When one or more LEDs in the VLP system happen to be shielded, work abnormally or even break, the positioning process will be interrupted. These issues are main barriers restricting the performance of the VLP system in terms of positioning accuracy, real-time ability and robustness, however, few studies have worked them out yet.

Driven by lack of prominent achievements at present, we improve our previous work [24] and eventually propose a better algorithm to solve those complex problems, realizing a satisfactory VLP system which takes the positioning accuracy, the real-time ability and the robustness into consideration at the same time. In our VLP system, the particle filter is used to quickly track the position of LED in the image through consecutive frames after detecting LED by using a LED detection algorithm. Then the positioning algorithm uses the obtained LED position to perform camera positioning to obtain the position of the camera, which does not use the particle filter. The particle filter can be combined with different positioning algorithms to improve the robustness of the VLP system without affecting the performance of the original positioning algorithm. In this paper, two main problems in VLP are considered. Firstly, for a VLP system, shielding effect and background interference are easy to occur in real life, which is the most significant factor affecting robustness. The proposed particle filter tracking algorithm can estimate the possible location of the target in the next frame image using the prior probability that is calculated based on the previous frames. Unlike Kalman filter whose uncertainty is restricted to Gaussian distribution, the particle filter is found to be able to deal with non-gaussian noise distribution, consequently, in cases that the sensor noise turns out to be jerky error, the latter still produces robust positioning result while the former offers prediction of position with leap [25]. Therefore, the shielding effect and blur situation can be handled exhilaratingly by using this algorithm. Secondly, most of the algorithms in previous research about VLP have high time complexity, whose computational cost is too large to ensure the real-time ability of the system. Since sprinkling particles near the target area are adopted by the particle filter, it can greatly reduce the computational cost to improve the real-time ability of the system. In our experiment, various situations are simulated to examine the performance of the system and the results show that our proposed VLP system achieves high robustness without affecting the positioning accuracy and the real-time ability. The remainder of this paper is organized as follows. Section 2 provides a detail derivation of the proposed positioning and tracking algorithm. The experimental setup and analysis are presented in Section 3. Finally, in Section 4, a conclusion is presented to summarize the work.

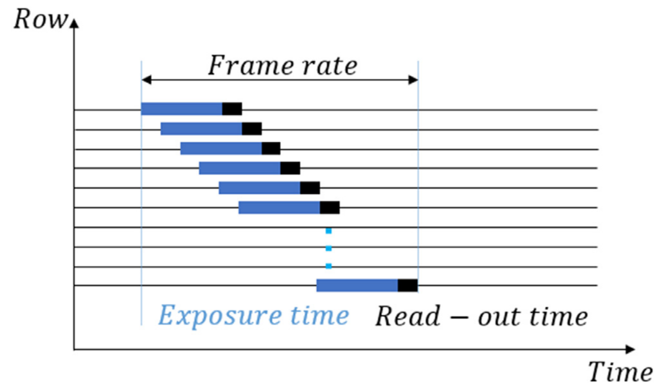


Fig. 1. Rolling shutter mechanism of the CMOS.

2. Theory

As is shown in Fig. 1, the working principle of Complementary Metal Oxide Semiconductor (CMOS) image sensor is called "Rolling Shutter Mechanism", which is utilized to realize LED-ID recognition by visible light positioning (VLP). In fact, the rolling shutter mechanism is to expose and read row by row, and read the data of the row out promptly after each row is exposed. Due to the rolling shutter mechanism, the bright and dark stripes which represent the modulated data will appear on the image captured by the CMOS sensor by turning on and off the LED light [25,26]. The detailed processing of LED-ID modulation and recognition has been described in our previous reports [25,26].

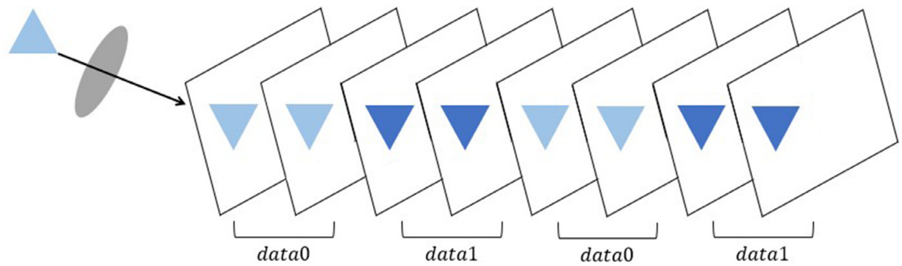


Fig. 2. The depicted sequence of camera images of a scene containing a blinking LED.

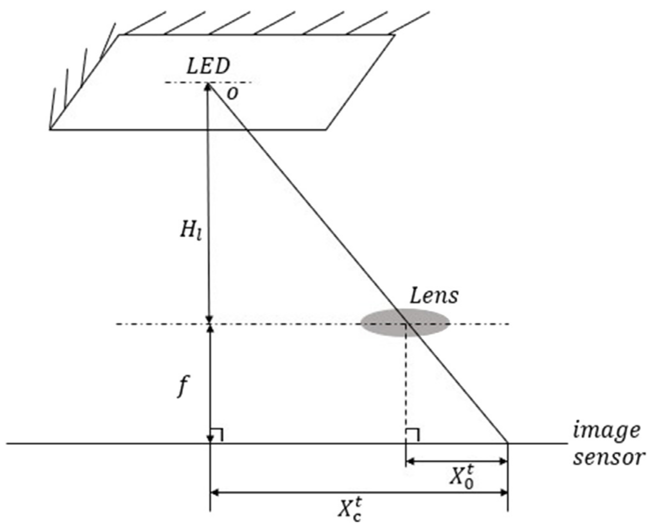


Fig. 3. The geometrical relationship between LED and image sensor.

As a matter of fact, the implementation of dynamic positioning and tracking is to analyze and search the captured image sequence to find the position with the highest similarity to the target. Based on this idea, the particle filter method is exploited to track the video target, which includes importance sampling, weight calculation and resampling. After detecting the LED in the first frame the proposed algorithm can make use of the target LED detected in the first frame to obtain the LED position in the following frames by the particle filter. In the following parts, the VLP positioning technology will be briefly introduced and the algorithm will be explained theoretically in detail.

2.1. VLP positioning technology

In the two-dimensional continuous image sequence, which is known as Fig. 2, the set of pixels which belong to LED is defined as $(x_i^t, y_i^t) \in L^t$, where the set of pixels which belong to LED at time t is denoted by L^t and the subscript i represents the ith pixel in the image [24].

In addition, the pixel coordinate of the LED $s_l(x^t, y^t)$ is assumed to be the center coordinate of LED in the image sequence. In this paper, as is shown in Fig. 3, the geometric relations in the positioning system are fully utilized to obtain the image sensor's world coordinate $z_l(t)$.

The relationship between the various system is shown in Fig. 4. The origin of image coordinate system is the point of intersection of camera's optical axis and the image sensor imaging plane, i.e. the center of midpoint of the image sensor imaging plane. The unit of the mentioned image coordinate system is mm, which belongs to physical unit. The unit of the pixel coordinate is pixel, which is described by its row and line. Therefore, their relationship are shown as follows dx and dy represent the unit conversion of two coordinate system, i.e. 1 pixel $= dy$ mm. Focused on the lens f, the size of each pixel on CMOS is dx and dy, the height H_l and the midpoint (x_0, y_0) of image sensor's imaging plane in pixel coordinate system is known. The process of calculating $z_l(t)(x_l^t, y_l^t)$ is as follows. Firstly, calculate the center coordinate $\left(X_0^t, Y_0^t\right)$ of LED at time t in the image coordinate system:

$$x^t = \frac{X_0^t}{dx} + x_0 \tag{1}$$

$$y^t = \frac{Y_0^t}{dy} + y_0 \tag{2}$$

Eqs. (1) and (2) can be rewritten in the matrix form as:

$$\begin{bmatrix} X_0^t \\ Y_0^t \\ 1 \end{bmatrix} = \begin{bmatrix} dx & 0 & -x_0 dx \\ 0 & dy & -y_0 dy \\ 0 & 0 & 1 \end{bmatrix} \begin{bmatrix} x^t \\ y^t \\ 1 \end{bmatrix} \tag{3}$$

By using the center coordinate (X_0^t, Y_0^t) of LED in the image coordinate, we can calculate the coordinate (X_c^t, Y_c^t) of the camera in the camera coordinate system:

$$\frac{X_0^t}{X_c^t} = \frac{Y_0^t}{Y_c^t} = \frac{f}{f + H_l} \tag{4}$$

The relationship between the camera coordinate system and the world coordinate system is shown in Fig. 5. We can rotate and translate the coordinate by formula (5) and realize positioning under any azimuth. The image sensor's world coordinate (x_l^t, y_l^t) is transformed from (X_c^t, Y_c^t) by a matrix:

$$\begin{bmatrix} X_c^t \\ Y_c^t \\ 1 \end{bmatrix} = \begin{bmatrix} cos\theta & sin\theta & 0 \\ -sin\theta & cos\theta & 0 \\ 0 & 0 & 1 \end{bmatrix} \begin{bmatrix} x_l^t \\ y_l^t \\ 1 \end{bmatrix} + \begin{bmatrix} T_X \\ T_Y \\ 1 \end{bmatrix} \tag{5}$$

where $\begin{bmatrix} T_X \\ T_Y \\ 1 \end{bmatrix}$ represents translation;θ represents the rotation angle between the world coordinate system and the camera coordinate system; where z_l^t denotes (x_l^t, y_l^t), which is calculated from formula (3) ∼(5). Defined that:

$$z_l^t = h\left(s_l, D_l\right) \tag{6}$$

where the lth coordinate of the LED in the world coordinate is represented by D_l and h stands for the mapping function.

2.2. Particle filter algorithm

Since the LEDs are detected in the first frame by using a LED detecting algorithm, the particle filter can estimate the posterior probability density in the current environment by obtaining the prior probability of the target signal LED in the previous time. In order to achieve real-time dynamic positioning and tracking, each frame of the image sequence needs to be continuously filtered and processed, which leads to excessive computational cost and poor real-time performance. However, provided that the feature of particle filter is used, the problem of excessive computational cost caused by real-time detection LED can be effectively solved. Compared with Kalman filtering and Bayesian prediction, the particle filter has better robustness in dealing with

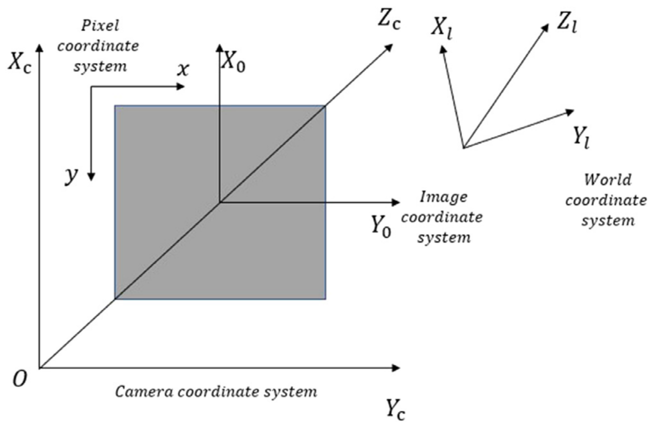


Fig. 4. World coordinate system, camera coordinate system, image coordinate system and pixel coordinate system.

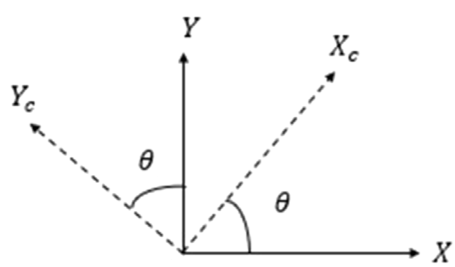


Fig. 5. The transformation model of camera coordinate system and the world coordinate system without considering translation.

non-gaussian and non-linear problems [27]. Therefore, the particle filter is utilized to estimate the LED position coordinates of the next frame, which maintains the positioning accuracy and the real-time performance of positioning algorithm.

In addition to the real-time ability of the system, there is a bigger problem to be solved in VLP that when shielding effect and background interference occur, the positioning is easy to fail. However, many studies only focus on real-time ability and ignore it. To solve this problem, the state observation model of particle filter is used by judging the similarity between the target model and the candidate model to realize the positioning of LED in shielding and interference.

2.2.1. The state space model

In order to achieve real-time dynamic positioning and tracking, two models need building when the LED signal is tracked. A model is called state transition model, which describes the rule of state transition and change at adjacent time. The other is called observation model, which describes the relationship between the state of the system and the observed information. The two models together form a state space model describing the dynamic positioning and tracking of LED, which is known as Fig. 6.

After processing the image sequence, the coordinate of LED is known in the pixel coordinate *s(k)*. The state transition equation is as follows:

$$z_l(k) = f\left(z_l(k-1)\right) + o_k \tag{7}$$

where $z_l(k)$ represents the true state at time k, o_k is the process noise and $f(.)$ is the mapping function. This state transition model describes the state transition $p(z_l(k)\,|z_l(k-1))$. In addition, the observation equation at time k is as follow:

$$y(k) = g\left(z_l(k)\right) + v_k \tag{8}$$

where $g(.)$ is the observation function which maps the true space into the observed space and v_k is the observation noise. The observation model describes the state likelihood probability $p(y(k)\,|z_l(k))$.

According to the Bayesian estimation theory, the prior probability distribution of the system is known. In other words, the position information of the LED in the first frame has been detected. After obtaining the new observation values, the posterior probability distribution $p(z_l(k)\,|y_{1:k})$ of the system state can be estimated recursively, where $y_{1:k} = [y(1), y(2), \ldots, y(k)]$. The initial value $z_l(0)$ is known, and the prior distribution $p(z_l(0))$ is also known:

$$p\left(z_l(0)\,|\mathrm{y}(0)\right) = p\left(z_l(0)\right) \tag{9}$$

Given that the posterior probability density at time k-1 is $p(z_l(k-1)\,|y_{1:k-1})$, and observation value is $y(k)$ at the current moment, the posterior probability density $p(z_l(k)\,|y_{1:k})$ can be obtained through two steps of prediction and update. The prediction model is:

$$p\left(z_l(k)\,|y_{1:k-1}\right) = \int p\left(z_l(k)\,|z_l(k-1)\right) p\left(z_l(k-1)\,|y_{1:k-1}\right) dz_l(k-1) \tag{10}$$

The updated model is:

$$p\left(z_l(k)\,|y_{1:k}\right) = \frac{p\left(\mathrm{y}(\mathrm{k})\,|z_l(k)\right) p\left(z_l(k)\,|y_{1:k-1}\right)}{p\left(y(k)\,|y_{1:k-1}\right)} \tag{11}$$

And $p\left(y(k)|y_{1:k-1}\right)$ can be calculated as follows:

$$p\left(y(k)|y_{1:k-1}\right) = \int p\left(y(k)\,|z_l(k)\right) p\left(z_l(k)\,|y_{1:k-1}\right) dz_l(k) \tag{12}$$

where $p\left(z_l(k)\,|z_l(k-1)\right)$ is given by formula (5); $p\left(y(k)\,|z_l(k)\right)$ is the observation likelihood function, which can be obtained formula (6).

2.2.2. HSV histogram

The state observation model determines how similar the image subregion of each particle is to the target template. The key to establish the observation model is to select the features of the target and measure the similarity between two frames in the sequence image [28]. The central position of the LED region is s_l from Section 2.1, and there are N pixels of $\{s_i\}_{i=1}^{N}$ in this region, then the HSV feature $p_u(s_l)$ of the LED can be expressed as:

$$p_u\left(s_l\right) = C\sum_{i=1}^{N} k(\|\frac{s_l - s_i}{h}\|)\delta[z_l\left(s_i\right) - u], u = 1, 2, \ldots, m \tag{13}$$

where $u = 1, 2, \ldots, m$ is the index of HSV space subregion; $\delta[z_l\left(s_i\right) - u]$ is a mapping function, which means that each pixel is mapped to that subregion in the feature space; $z_l\left(s_i\right)$ is the pixel value of s_i; C is the normalization factor, making $\sum_{u=1}^{m} p_u\left(s_l\right) = 1$; $k(r)$ is the weight function, which is used to quantify the contribution of HSV components to the tracking algorithm:

$$\mathrm{k}(\mathrm{r}) = \begin{cases} 1 - r^2, & r < 1 \\ 0, & others \end{cases} \tag{14}$$

where r represents the center position of the LED region.

After obtaining the HSV histogram of the target LED template and the target candidate template respectively, the Bhattacharyya coefficient can be used to measure their similarity. Suppose the weighted HSV histogram of the LED template is $p\left(s_l\right)$, which is equal to $\{p_u\left(s_l\right)\}_{u=1,2,\ldots,m}$, and the weighted HSV histogram of the target candidate template at time t is q, which is equal to $\{q_u\}_{u=1,2,\ldots,m}$, the Bhattacharyya coefficient between $p_u\left(s_l\right)$ and q_u is:

$$\rho\left[p\left(s_l\right), q\right] = \sum_{u=1}^{m} \sqrt{p_u\left(s_l\right) q_u} \tag{15}$$

The bigger the value of Eq. (13) is, the higher the HSV similarity between the target template and the target candidate template is.

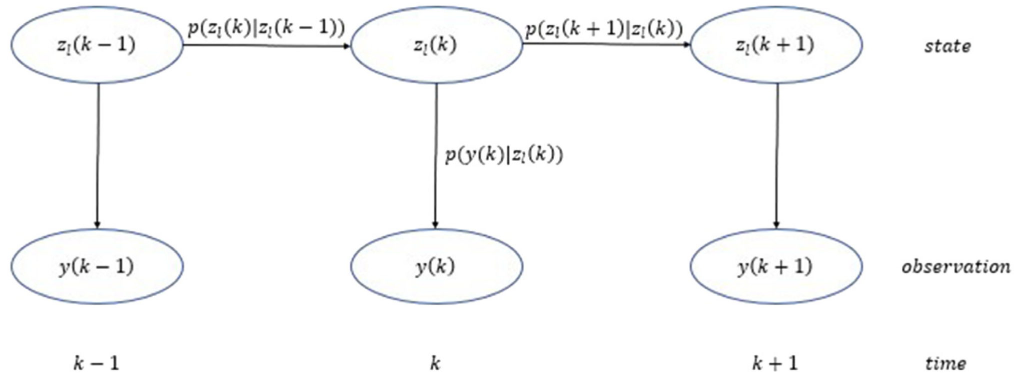


Fig. 6. The state space model.

The distance function between the two histograms of the real target and the target to be tracked is now defined as:

$$\mathrm{d} = \sqrt{1 - \rho\left[p\left(s_l\right), q\right]} \tag{16}$$

Then the weight of each particle is:

$$\pi^n = \frac{1}{\sqrt{2\pi}\sigma}\exp\left(-\frac{d^2}{2\sigma^2}\right) = \frac{1}{\sqrt{2\pi}\sigma}\exp\left(-\frac{1-\rho\left[p\left(s_l\right), q^n\right]}{2\sigma^2}\right) \tag{17}$$

where $\pi^n \in [0,1]; q^n$ is the color model of the Nth particle in the tracking result target at time k, making $q^n = \sum_{u=1}^{m} q_u$.

2.2.3. Sequence importance sampling

The LED dynamic tracking is a nonlinear non-gaussian system, so it is difficult to obtain the optimal solution for the state estimation problem. Particle filter based on Monte Carlo simulation is a method for the optimal solution of Bayesian estimation time by using of a system approximation of the prior probability and posterior probability of a set of weighted samples, which does not require the state transition model and observation model are linear as well as does not require the noise is gaussian [29]. Therefore, it can effectively solve the LED dynamic positioning problem of state estimation. Sequence importance sampling is a common sampling technique in Monte Carlo method, which computes the weight of importance in the form of recursion, thus avoiding changing the sample set of the state sequence at the previous time.

Assume that $\{z_l(k)_i, w_k^i\}_{i=1}^N$ is a random sampling of the posterior probability density $p\left(z_l(k)|y_{1:k}\right)$, where $\left\{z_l(k)_i\right\}_{i=1}^N$ is a set of sample points with weight $\left\{w_k^i\right\}_{i=1}^N$, and the posterior probability density function at the moment k is approximately:

$$p\left(z_l(k)|y_{1:k}\right) \approx \sum_{i=1}^{N} w_k^i \delta\left(z_l(k) - z_l(k)_i\right) \tag{18}$$

In the formula, $\delta(.)$ is the Dirac function and w_k^i is the weight, and it satisfies:

$$\sum_{i=1}^{N} w_k^i = 1 \tag{19}$$

2.2.4. Resampling algorithm

The SIS algorithm replaces the integral operation with the sample mean to achieve recursive Bayesian estimation. However, the SIS algorithm has a serious problem of sample regression. To solve this problem, a resampling algorithm is introduced, which resamples and generates N equal weight particles based on current particles. The basic idea of the resampling algorithm is to discard particles with smaller weight for each iteration, copy the particles with larger weight, and set the weight of the newly sampled particles to 1/N.

The effective particle sampling coefficient is defined as:

$$N_{eff} = \frac{1}{\sum_{i=1}^{N}\left(w_k^i\right)^2} \tag{20}$$

When the particle sampling coefficient N_{eff} is less than a certain threshold value, it is considered that particle degradation occurs and resampling is needed.

2.2.5. Implementation of the algorithm

In general, the basic particle filter algorithm mainly includes three parts: importance sampling, weight update and resampling. The algorithm flow chart is shown in Fig. 7 and the specific implementation steps of the algorithm are as follows:

• Step 1 initialization:

(1) In this paper, the algorithm adopts the first-order autoregressive model $z_l(k) = Az_l(k-1) + v_{k-1} + Co_{k-1}$, so the initial distribution $p\left(z_l(0)\right) \sim z_l(1) = Az_l(0) + v_0 + Co_0$.

(2) At time k = 0, N initial particles are sampled from the initial distribution $p(z_l(0))$, and the weight of each particle is 1/N, denoted as $\{z_l(0)_i, 1/N\}_{i=1}^N$.

• Step 2 importance sampling:

It is assumed that the particle set used to approximate the posterior probability distribution of the state at time *k*-1 is $\{z_l(k-1)_i, w_{k-1}^i\}_{i=1}^N$, and the prior particle set $\{z_l(k)_i, w_{k-1}^i\}_{i=1}^N$ at time *k* is obtained by resampling each particle in this set according to the importance distribution function $p\left(z_l(k)|y_{1:k}\right)$.

• Step 3 weight update:

(1) After obtaining the observed value $y(k)$ at time k, the observation likelihood function $p\left(y(k)|z_l(k)\right)$ can be calculated.

(2) After the importance sampling the weight of each particle in the particle set $\{z_l(k)_i, w_{k-1}^i\}_{i=1}^N$ is updated,

$$w_k^i \propto w_{k-1}^i p\left(z_l(k)|y_{1:k}\right)$$

And the normalized particle weight: $w_k^i = w_k^i / \sum_{i=1}^N w_k^i$.

The color distribution eigenvalues of each particle are:

$$q_u^i = C\sum_{j=1}^{M} k(\|\frac{y_i - y_j}{h}\|)\delta[z_l\left(y_j\right) - u], \mathrm{j} = 1, 2, \ldots, \mathrm{M}$$

where j represents that each particle is calculated by M pixels to obtain the color eigenvalue. Combined with the color eigenvalue information of the real target, the Bhattacharyya coefficient can be calculated:

$$\rho\left[p\left(s_l\right), q^i\right] = \sum_{u=1}^{m}\sqrt{p_u\left(s_l\right) q_u^i}$$

the formula of particle weight calculation is as follows:

$$w_k^i = \frac{1}{\sqrt{2\pi}\sigma}\exp\left(-\frac{d^2}{2\sigma^2}\right) = \frac{1}{\sqrt{2\pi}\sigma}\exp\left(-\frac{1-\rho\left[p\left(s_l\right), q^i\right]}{2\sigma^2}\right)$$

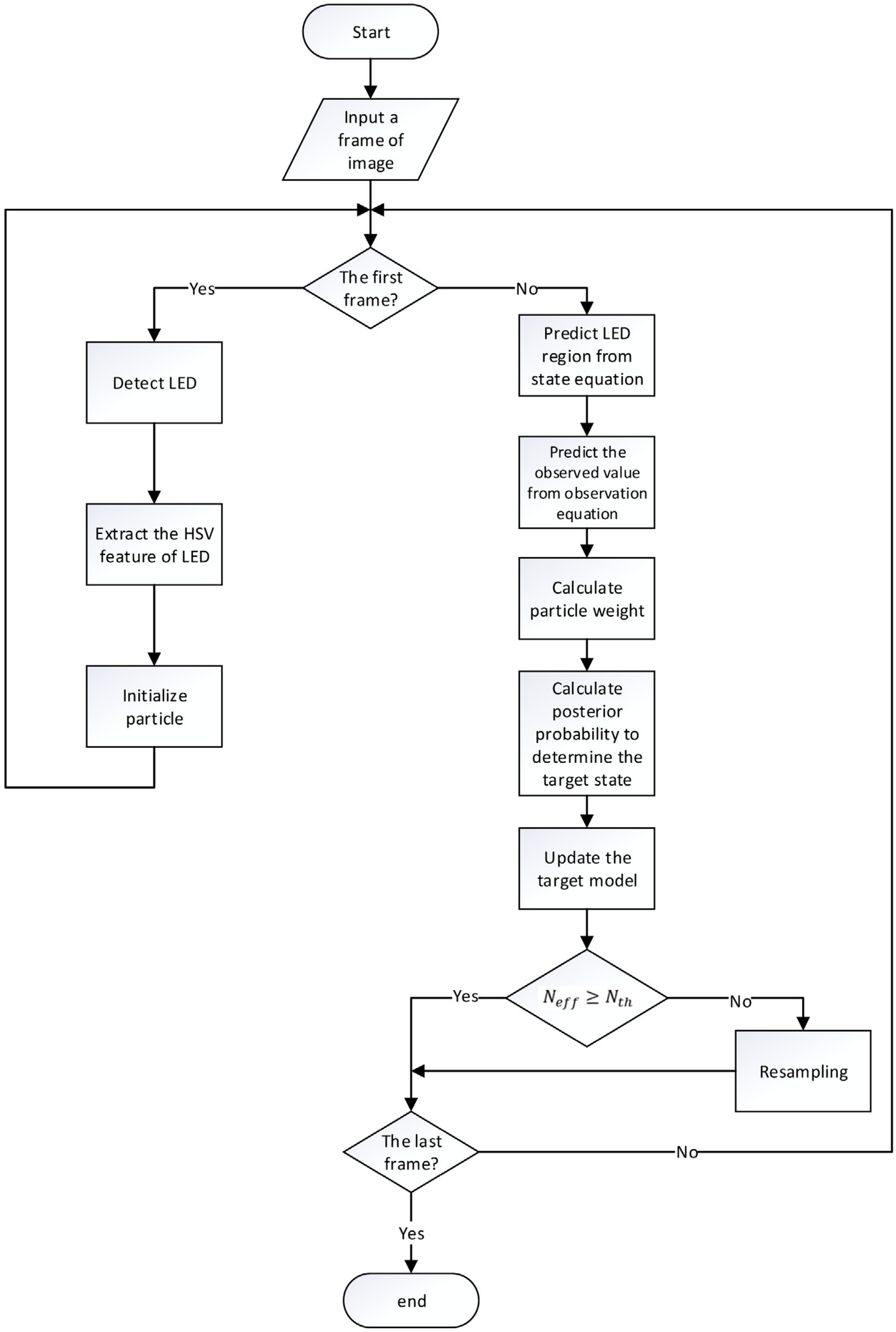


Fig. 7. The particle filter algorithm.

• Step 4 state estimation:

The weighted sum method is used to estimate the state at time k:

$$z_l(k) = \sum_{i=1}^{N} z_l(k)_i \, w_k^i$$

• Step 5 resampling:

N_{eff} is calculated as follows: $N_{eff} = 1/\sum_{i=1}^{N} \left(w_k^i\right)^2$

If $N_{eff} \leq N_{th}$, the particle set $\{z_l(k)_i, w_k^i\}_{i=1}^{N}$ at time k is resampled to obtain the new particle set $\{z_l(k)_i, 1/N\}_{i=1}^{N}$.

• Step 6 let $k = k + 1$, go to step 2.

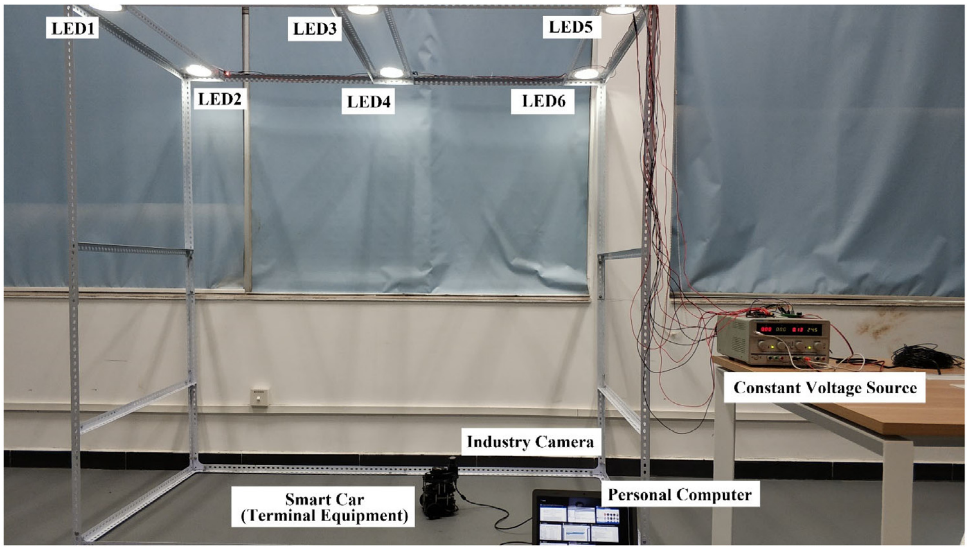


Fig. 8. Hardware of the proposed system configuration.

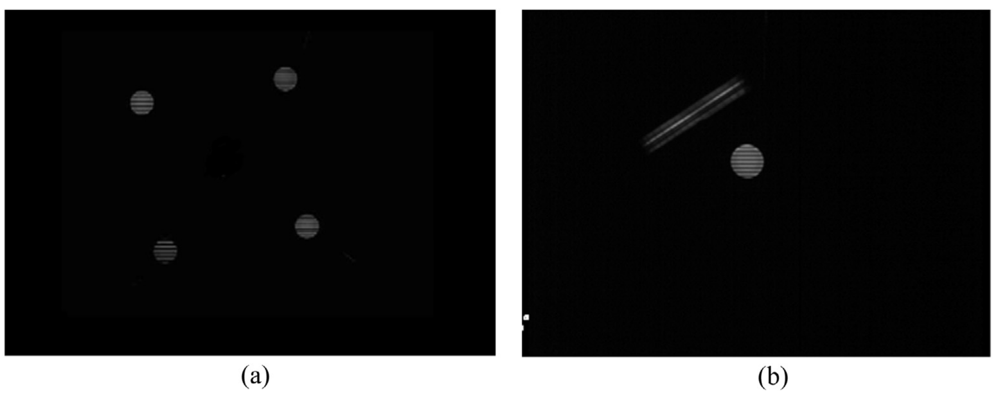


Fig. 9. Images after adjusting exposure time: (a) images with four LEDs in the field of view of the industry camera; (b) images with one target LED.

3. Experimental setup & result analysis

3.1. Experimental setup

The experimental platform is shown in Fig. 8, including a constant voltage source, six LEDs, an industry camera, a smart car and a computer (Dell Inspiron 5557, Windows 10, 4G RAM, Intel (R) Core (TM) i5-6200 CPU @ 2.4 GHz). Constant voltage source supplies power to LEDs. The LED emits the optical signal as a transmitter and the industry camera receives this signal as a receiver. The smart car is a carrier for the industry camera, simulating mankind indoor movement. The computer processes receiving image signals with our algorithm to detect the LEDs and position the camera in real time. Besides, open source computer vision library (OpenCV 3.2.0) is used to process receiving images with C++ language as the software system.

As can be seen from Fig. 8, six LEDs are located on the ceiling of the system configuration in an experimental platform with the size of 210 cm×110 cm×200 cm and their coordinates (in cm) are (10, 10, 200), (10, 100, 200), (105, 10, 200), (105, 100, 200), (200, 10, 200) and (200, 100, 200), respectively. Besides, specifications of the industry camera, experimental platform, LEDs, the smart car and the circuit board are shown in Table 1.

We recorded a video sequence with the industry camera introduced above to better explain the proposed algorithm and the experimental result. In the experiment, the terminal (the smart car) keeps moving throughout the process and its trajectory is controlled by a mobile phone through Bluetooth. After adjusting the exposure time of the camera, only LEDs and other luminous objects, such as light-emitting tubes on the ceiling of the room, are left in the images, which are shown in Fig. 9(a). LEDs are treated as the foreground and other luminous objects are regarded as disturbing factors as the background. Applying the relationships between coordinate systems, the region of interest (ROI) shrinks to a small region so that we can realize positioning with the coordinate of only one LED (called target LED, as a signal source). In other words, there is no need to get the coordinates of all four LEDs, the terminal equipment can be located so long as one of them is obtained, which decreases the computational cost. Therefore, to simplify the experiment, only one LED is taken into consideration to validate the performance of our algorithm, shown in Fig. 9(b).

3.2. Result and analysis

3.2.1. Robustness performance

Robustness is an important index to judge the stability of a system and reflects the performance of the proposed algorithm. As for dynamic positioning and tracking system based on visual visible light communication, shielding effect and background interference are the hugest two obstacles to robustness in practical situation and may make the positioning fail. Shielding effect means the target LED, which is also called the signal source that carries modulated information, is masked in different degrees. What is more, background interference occurs when light-emitting tubes or other luminous objects get into

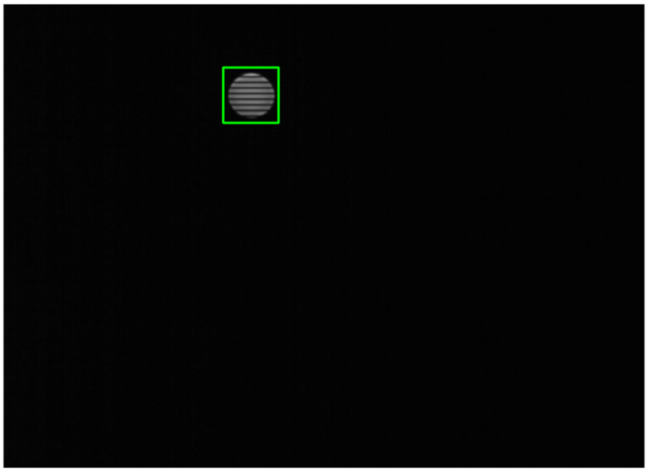
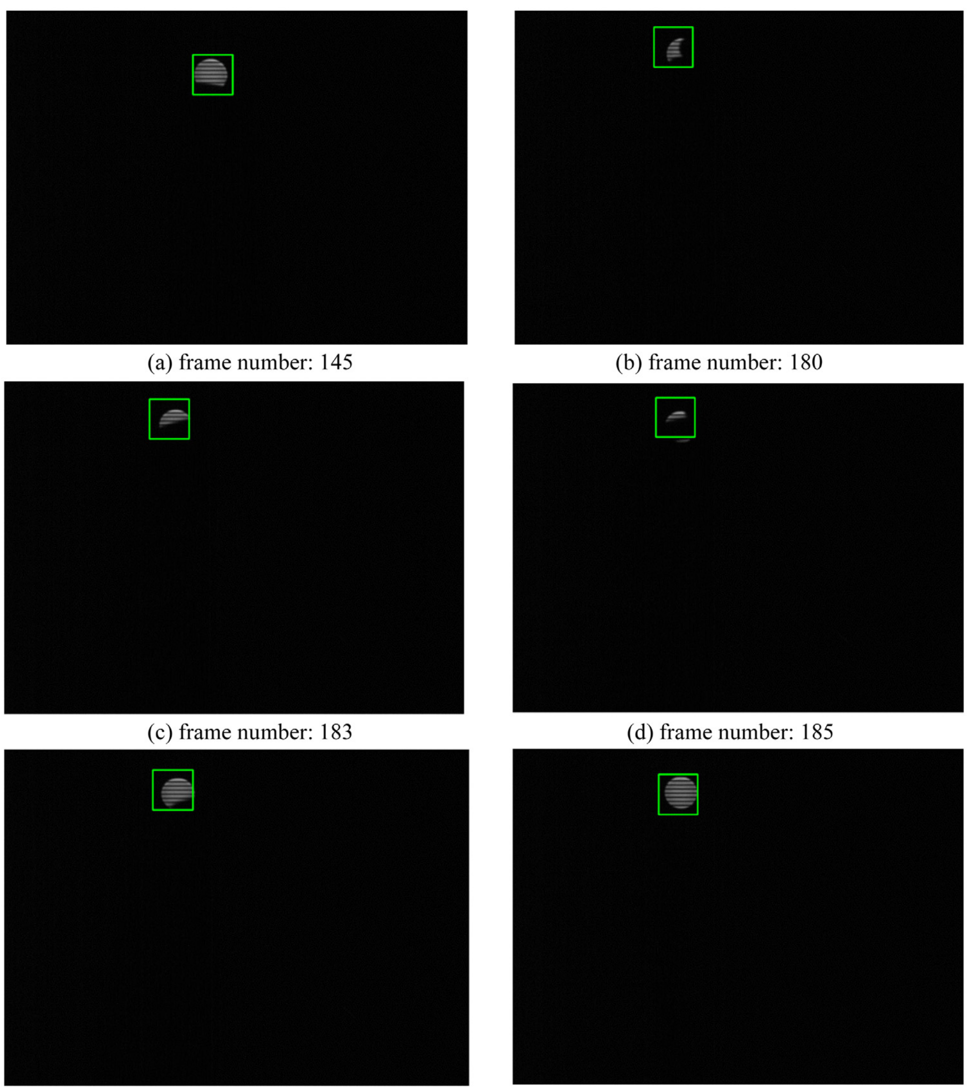


Fig. 10. Complete signal source detection without interference or shielding.

the camera's field of view. These disturbances have a bad effect on tracking the signal source and even affects the success of extracting the target LED region from the images, causing the signal source's modulated information cannot reach the receiver completely and accurately. Therefore, positioning and tracking the terminal would fail. To test the robustness of the proposed algorithm, the real situation is simulated, including complete signal source in images without interference or shielding, signal source shielding in different degrees and background light-emitting tubes interference.

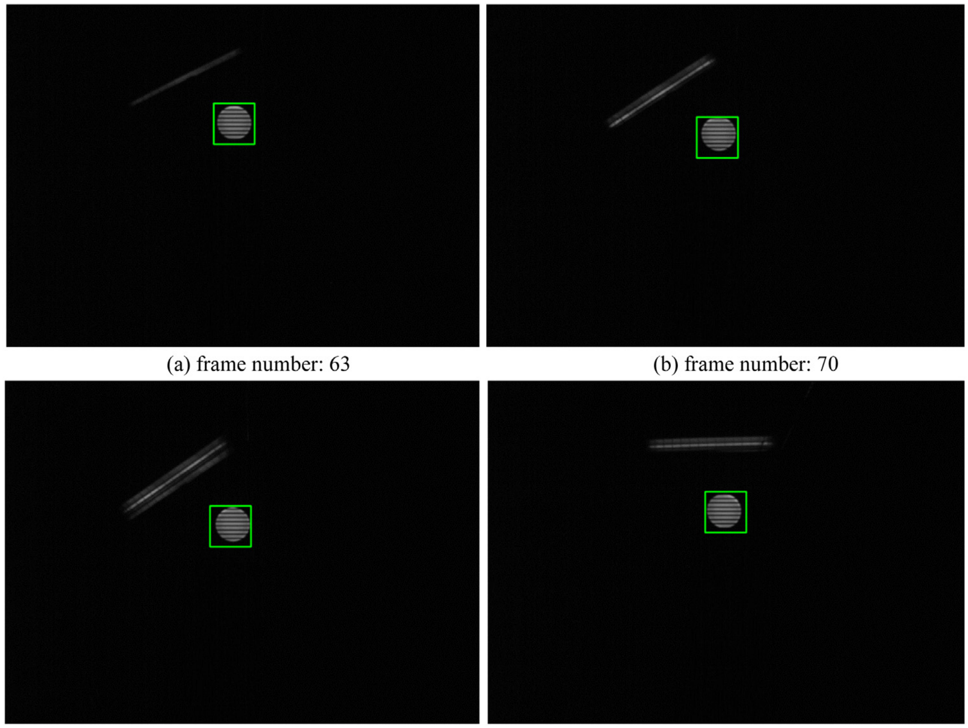
Firstly, in most cases, the signal source is complete in the camera's field of view with few interferences. In this situation, full valid data of particles can be obtained and the region of the target LED is extracted successfully and completely. As can be seen from Fig. 10, the proposed algorithm can track and position the target LED accurately with small errors, in other words, the proposed algorithm possesses high positioning accuracy.

Moreover, as is shown in Fig. 11, extracting the region of signal source and positioning are affected accordingly when the target LED is masked to varying degrees. During the process of our experiment, shielding effect begins at the 145th frame. The target LED is masked with a small portion in this frame and is extracted and located accurately with tiny errors. Then in the 180th, 183th and 185th frames, most part of the target LED is shielded, although the center of the extracted area has a slight deviation from the center of the target LED, the error range is acceptable. Next, shielding effect ends at the 187th



(a) frame number: 145
(b) frame number: 180
(c) frame number: 183
(d) frame number: 185
(d) frame number: 187
(e) frame number: 189

Fig. 11. Tracking performance when shielding effect occurs (the target LED is masked to varying degrees).



(a) frame number: 63 (b) frame number: 70

(c) frame number: 79 (d) frame number: 96

Fig. 12. Tracking performance when background interference occurs.

frame where small part of the signal source is masked and after that, the target LED can be located accurately with small errors again, shown in Fig. 11(e).

Furthermore, background interference is another main obstacle in the dynamic positioning and tracking system which is based on visual visible light communication. In our experiment, light-emitting tubes are used as the interference item, which is also the same with practical situation. As can be seen in Fig. 12, a light-emitting tube appears in the camera's field of vision as a background interference. Fig. 12 shows that the proposed algorithm has a good performance when there is disturbance in the background.

3.2.2. Accuracy performance

The other main measure factor of the high-speed dynamic positioning and tracking method is the tracking accuracy. Tracking error is defined as:

$$D = \sqrt[2]{\left(x - x_r\right)^2 + \left(y - y_r\right)^2} \tag{21}$$

$$error\,of\ x\,(y) = \left|value_{calculated} - value_{actual}\right| \tag{22}$$

where (x, y) represents the calculated position obtained by the proposed algorithm and (x_r, y_r) represents the actual position. In the recording video sequence, one hundred successive frames are chosen randomly to process to evaluate the accuracy of the proposed algorithm. The result of tracking is shown in Fig. 13 where the red dot represents the actual coordinate and the blue dot is the calculated coordinates for each sampling with the proposed algorithm. As can be seen from the result, the performance of the tracking is well for most samples with small errors. To better illustrate the result and show the performance of the proposed algorithm, Fig. 14 shows the $error\,of\ x$ and $error\,of\ y$ coordinates, where the blue solid line represents $error\,of\ x$ and purple dotted line represents $error\,of\ y$. Average $error\,of\ x$ coordinate is 2.15 cm and average $error\,of\ y$ coordinate is 1.73 cm.

Fig. 15 shows the tracking error D calculated by the definition of tracking error. As can be seen that, the maximum tracking error D is 6.09 cm, and average tracking error D is 2.95 cm, which denotes that the LED detection is so accurate that the positioning accuracy of the positioning algorithm is not affected by the tracking algorithm. If the tracking algorithm has a large tracking error on the LED position in the LED detection, the positioning accuracy obtained by the positioning algorithm using the obtained LED position will be greatly reduced in the camera positioning. There are many reasons for the tracking error, such as image noise, shielding effect, background interference, the degradation problem of particles, the problem of inhomogeneous resampling, etc. However, it is important that in most practical applications of dynamic positioning and tracking system, such errors are acceptable. Therefore, the proposed algorithm has a good tracking and positioning performance.

To further demonstrate the performance of our proposed algorithm, cumulative distribution function (CDF) is introduced. CDF is the integral of the probability density function which can describe the probability distribution of $tracking\,error\ D$, $error\,of\ x$ and $error\,of\ y$ coordinates, shown in Fig. 16. In CDF curve, when the ordinate value is fixed, the smaller the abscissa, also the error value, the more accurate the algorithm performs. As indicated by the curves, more than 85% $tracking\,error\ D$, $error\,of\ x$, and $error\,of\ y$ is less than 3.06 cm, 4.16 cm, and 3.35 cm, respectively. It means that if 85% is assumed as an acceptable service coverage rate, the proposed algorithm will be able to deliver an accuracy of 3.06 cm. Therefore, we can conclude that the proposed algorithm has a good accuracy.

3.2.3. Real-time performance

Processing time of the program and complexity of the algorithm significantly affect real-time performance of dynamic tracking and positioning. Dynamic tracking and positioning will lose its meaning if the running time is too long. Because the terminal keeps moving throughout the process, theoretically, the terminal has already moved to the next position when the coordinate is calculated. In other words, the coordinates obtained are always the last position of the terminal equipment. However, in most practical applications, such errors will not have much adverse impact on the realization of tracking and positioning so long as the program's processing time is short enough.

Table 1
Parameters of the experimental platform.

Camera specifications	
Model	MV-U300
Spectral response range/nm	400~1030
Resolution	800 × 600
Frame rate/FPS	46
Dynamic range/dB	>61
Signal-to-noise Ratio/dB	43
Pixel(H × V)	2048 × 1536
Pixel size/μm^2	3.2 × 3.2
Time of exposure/ms	0.0556-683.8
Sensitivity	1.0V/lux-sec 550 nm
Optical filter	650 nm Low pass optical filter
Type of shutter	Electronic rolling shutter
Acquisition mode	Successive and soft trigger
Working temperatures/°C	0-50
Support multiple visual software	OpenCV, LabView
Support multiple systems	Vista, Win7, Win8, Win10
Experimental platform specifications	
Size (L × W × H)/ cm^3	210 × 110 × 200
LED Specifications	
Coordinates (x, y, z)/cm	LED1(10, 10, 200) LED2(10, 100, 200) LED3(105, 10, 200) LED4(105, 100, 200) LED5(200, 10, 200) LED6(200, 100, 200)
Diameter of each LED/mm	150
Power of each LED/W	6
The half-power angles of LED/deg($\varphi_{1/2}$)	60
Smart car specifications	
Single-chip	STC89C52RC
Weight/g	1200
Remote control	Bluetooth, Wifi
Circuit board specifications	
Drive chip	DD311
Drive current/A	0.1
Drive voltage/V	28

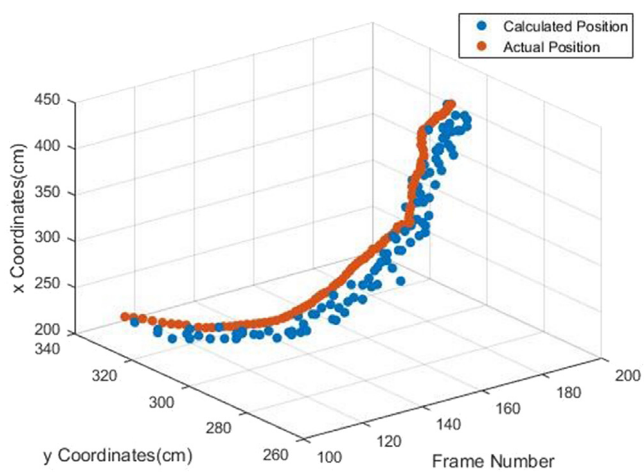


Fig. 13. The calculated coordinate value and actual coordinate value of the terminal.

In our experimental environment, one hundred successive frames of the whole process are chosen randomly to obtain the average processing time t and learn that it is 0.021 s, demonstrating that the computational cost required for particle filter is so small that the positioning algorithm is not affected by the tracking algorithm and can still have good real-time performance. If it takes 10 s for the tracking algorithm to obtain the position of the LED in the LED detection, the camera

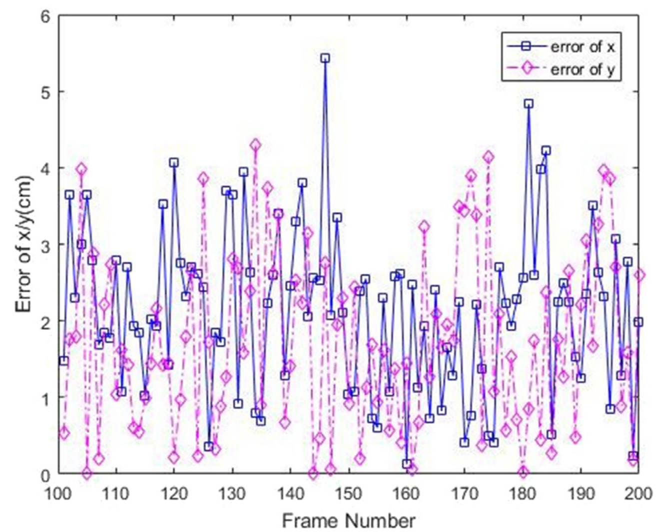


Fig. 14. Error of position value of x and y coordinates.

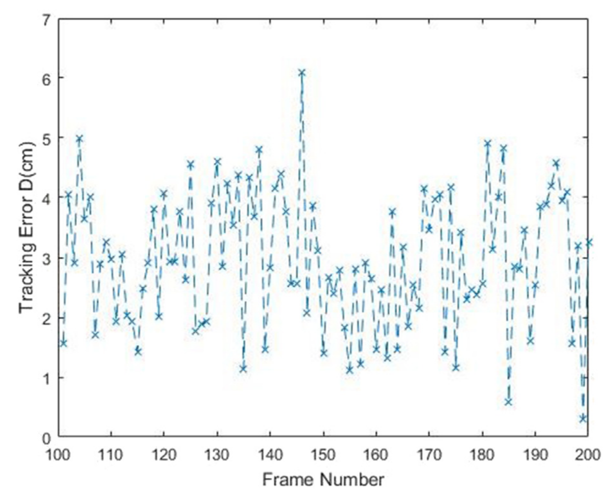


Fig. 15. Tracking error D of the terminal.

position obtained by the positioning algorithm using the obtained LED position at this time is the camera position before 10 s, which indicates that the VLP system does not have real-time performance and cannot be applied to real life. Compared to our previous works in the field of tracking and positioning, [24] for instance, whose running time is 0.162 s, the proposed algorithm of this paper is much faster. Although the accuracy of particle filter tracking algorithm is obviously lower than optical flow detection and Bayesian forecast algorithm in [24], in most practical applications of tracking and positioning system, the error of a few centimeters is acceptable and what' important is that the processing time of the proposed algorithm is only one eighth of that in [24]. Therefore, it can be concluded that the proposed algorithm has a good real-time performance.

4. Conclusion

In this paper, a high-speed dynamic positioning and tracking method based on VLP system is proposed, using the proportional relationships between different coordinate systems to locate the terminal equipment. The proposed method can solve the main problems in the field of

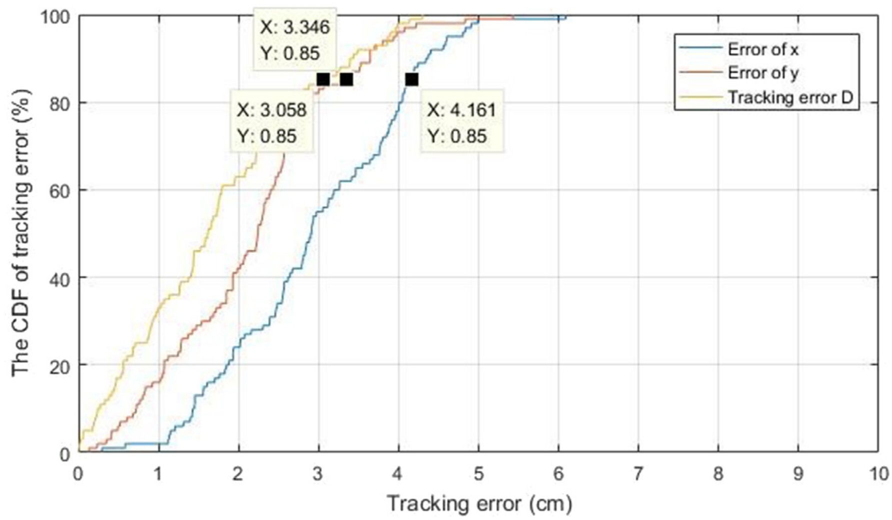


Fig. 16. The cumulative distribution function (CDF) of tracking error.

VLP. Particle filter algorithm has a good effect on dealing with non-gaussian noise distribution. In actual application, the sensor is prone to produce noise to disturb the target tracking. However, the proposed algorithm can still produce strong positioning results. Therefore, the shielding effect and blur situation can be effectively solved by the algorithm. Besides, maximum a posteriori estimation is used to remove the background interference by the particle filter algorithm. However, in our previous work [24], the optical flow method is still affected by the background light source and the Kalman filter cannot effectively deal with the blur situation. Therefore, we improve our previous work by proposing a better algorithm. The particle filter algorithm is applied to track the target signal source in motion state and all the three components of HSV histogram are taken into consideration simultaneously to enhance real-time ability and robustness, making it more feasible in a practical scenario with various interferences.

As for experiment results, the particle filter can provide an accuracy of 2.95 cm, and average computational time for each frame is only 0.021 s, demonstrating that the use of particle filter in LED detection does not burden the VLP system. Moreover, shielding effect and background interference are added to get closer to the actual situation and results show that the terminal equipment can still be located accurately, maintaining a good stability. All these results prove that the combination of particle filter and positioning algorithm has a good performance in terms of positioning accuracy, real-time ability and robustness, which has broad application prospects.

Acknowledgments

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