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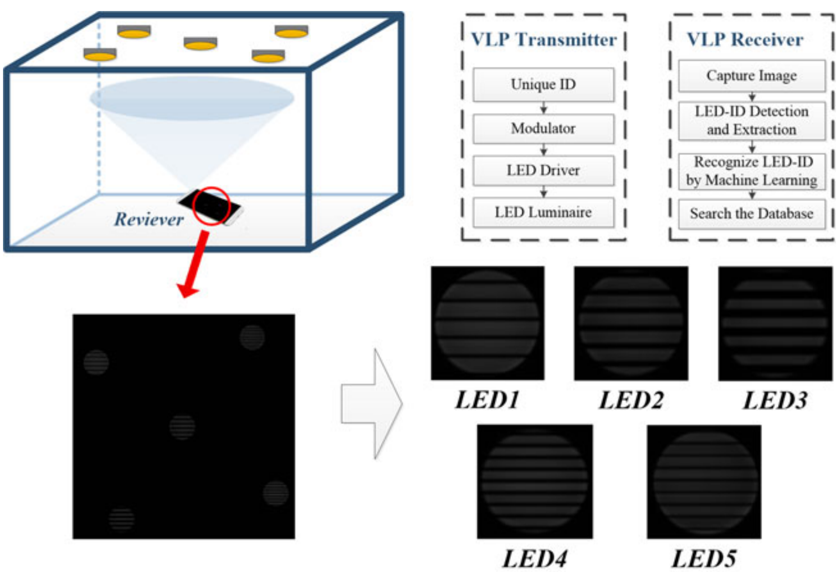

The process of the LED-ID detection and recognition

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The LED-ID Detection and Recognition Method Based on Visible Light Positioning Using Proximity Method

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Abstract: Complementary metal-oxide-semiconductor (CMOS) sensor based visible light positioning (VLP) has been widely studied in recent years due to its high robustness and high precision. In most researches about CMOS sensor based VLP, researchers always focus on the high-precision positioning algorithm but ignore that the accuracy of LED-ID detection and recognition plays a more important role in a VLP system. Without the correct recognition of LED-ID, the positioning algorithm would be meaningless no matter how effective it is. In addition, high-precision positioning is not required in most applications since it is enough for people to know just the approximate location. To solve these problems, in this paper, an LED-ID detection and recognition method based on visible light positioning using proximity method is propose. Different from the traditional LED-ID coding and decoding method, we create different features for different LED-ID, and use a machine learning method to identify the LED-ID once the feature extraction and selection of the LED image is achieved with an image processing method. It is the first time the machine learning method is used for LED-ID recognition in VLP. Moreover, we use a proximity-based positioning method to get the approximate location since it is easy to obtain once the LED-ID is recognized. The studies we have demonstrated shows that the proposed method can achieve high LED-ID recognition rate, and provide enough unique LED-ID for variable large-scale indoor VLP system. Furthermore, with the development of camera technology, the number of the unique LED-ID and the maximum recognizable distance would increase. Therefore, this scheme may be considered as one of the useful LED-ID detection and recognition method for visible light positioning in the future.

Index Terms: Visible light positioning (VLP), machine learning, LED-ID feature extraction and selection, proximity, CMOS image sensor, image processing.

1. Introduction

In recent years, with the development of economy and the improvement of technology, the demand for indoor navigation and positioning is also increasing, such as indoor service robots, indoor parking, indoor location-based services(LBS). However, the traditional indoor positioning methods, such as wireless local area network (WLAN), ZigBee, Bluetooth, infrared positioning, ultrasonic positioning, could only deliver positioning accuracy of tens centimeters to even few meters, and they are also easily disturbed by electromagnetic waves [1]–[3]. Therefore, a high accuracy indoor positioning method based on visible light communication (VLC) is put forward.

Indoor positioning system based on VLC can be divided into two modes: one is the Photodiode-based (PD-based), the other is the image-sensor based [4]–[6]. A PD-based positioning systems are usually positioned by receiving the light intensity of different LEDs, it cost less but it is not stable. With the interference of the background light or the reflection of the wall or furniture, the positioning accuracy would fall. Different from the PD-based method, the ambient lights will not affect the LED projects on the captured image directly. In the image-sensor based VLP system, the LED project on the image is treated as the foreground and the ambient light would be the background, so it is easy the extract the foreground by using the image processing method and reduce the interference of the ambient light. Therefore, comparing with two modes of the VLP system, the image-sensor based has a better anti-interference ability. To date, VLP based on image-sensor has been deeply explored and the positioning accuracy can reach to centimeters. For example, in [7], Ran Zhang *et al.*, put forward a method of using one LED and its geometry to achieve an image-sensor based VLP system, and the average positioning accuracy is 17.52 cm. In [8], Jae-Yoon Kim *et al.*, achieve the positioning accuracy to 6.5 cm with two LEDs. In [9], a SVD-based positioning method is put forward, this method needs three LEDs for the positioning algorithm and the accuracy of the positioning system is 12 cm. In [10], Wen-De Zhong *et al.*, proposed a sensor fusion based VLP system, by employing image sensor and motion sensors to get the rotation matrix, and using a sensor fusion algorithm to obtain the receiver's position and orientation. The positioning accuracy is about 10 cm. In [11], an image sensor based VLP algorithm is put forward, which could achieve an accuracy of 0.001 m by using the geometrical relationship of the reference LEDs and the LED images. In Ref [7]–[11], the proposed positioning algorithm could achieve high positioning accuracy, but they didn't discuss the LED-ID detection and recognition in detail. The detection and recognition of the LED-ID in a VLP system is more important than the positioning algorithm. Because once the LED-ID cannot be identified correctly, the positioning algorithm would be meaningless no matter how effective it is. In Ref [22], the data is packed into a data packet to transmit, and can achieve 32 bits or 64 bits payload one time. But only when a complete data packet could be captured by the camera, the data could be received and decoded successfully. With the distance between the transmitter and terminal increase, the area of the LED project would decrease, and a complete data packet might not be included. In our previous work in [12], we employed the similar method as Ref [22] and found that the maximum transmitted distance is only 50 cm, which means the method is not suitable for the VLP system. But in many image sensor based VLP researches, the LED-ID identification is only described simply or only discuss few LEDs, a specific and useful scheme of LED-ID detection and recognition for image sensor based VLP system is rarely given in the existing reports. In Ref [4] and [7], the LED-ID recognition method has been proposed. They modulated the data by the OOK method and pack the data into a data packet like Ref [22] and [12], but with fewer bits. And the data could be received and decoded only if the captured LED image include a complete data packet. But this method is not suitable for the long-distance case because the data packet might not complete once the distance between the LED and the camera increase. In Ref [23], a reference light source discrimination scheme by employing metameric light sources is proposed. In order to meet the needs of the indoor lighting, the color coordinates should be determined by the international commission on illumination (CIE). Meanwhile, comparing with other scheme, the scheme proposed in [23] cost more in hardware and is more complex in calculation.

In this paper, we propose a LED-ID detection and recognition method based on visible light positioning using proximity method. In reality, a centimeter-level positioning accuracy is not required.

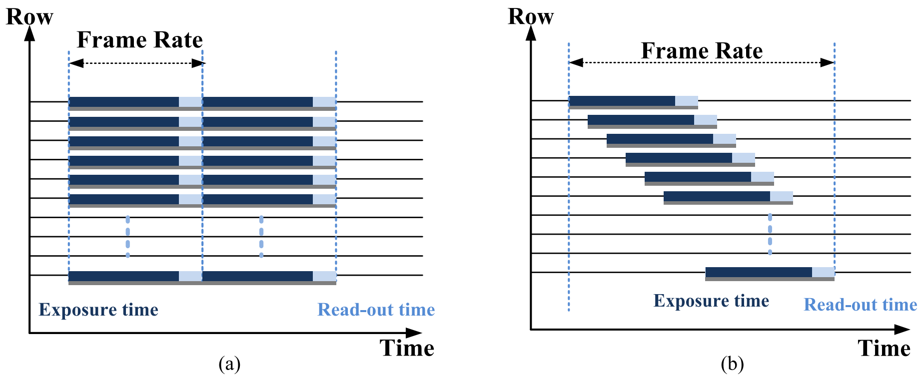

Fig. 1. Schematic diagrams of the (a) global shutter of the CCD sensor; (b) rolling shutter of the CMOS sensor.

So we employ a proximity based positioning method in this paper. The approximate position of the receiver can be determined once the LED-ID is identified correctly. Different from the traditional LED-ID encoding and decoding methods, we treated the LED-ID detection and recognition problem as a classify problem in machine learning filed. We modulate each LED with a variable frequency and duty-ratio Pulse-Width Modulation (PWM) method so that different LED-ID would have three different features: the number of the bright stripes, the area of the LED image, and the ratio of the bright stripe's width to both the bright and dark stripes' width (duty-ratio of the bright stripes). And once the LED image is captured by a CMOS image sensor, an image processing method is used to extract the features of LED-ID. In order to use the extracted features to identify the LED-ID, a Fisher classifier and a linear support vector machine are used. By off-line training for the classifiers and online recognition of LED-ID, the scheme proposed could improve the speed of LED-ID identification and improve the robustness of the system. As the experiment result shows, the proposed method could label roughly 1035 unique LEDs, and the maximum distance could reach to 6 m. It is enough for a large-scale applications. And as the improvement of camera technology, the number of the recognizable LEDs would also increase. Furthermore, the proposed method could also combine with the high accuracy positioning algorithm such as proposed in Ref [7]–[10] to apply in a large-scale application, which is not discussed in our work. Thus, the proposed scheme could be considered as one of the reliable LED-ID recognition method for indoor visible light positioning in the future.

2. System Principle

2.1 Principle of Using CMOS Sensor in VLC

2.1.1 Rolling Shutter Mechanism: The working principle of CMOS sensors and Charge Coupled Devices (CCD) sensor are illustrated in Fig. 1. With a CCD sensor, all pixels on the sensor are exposed at the same time, and the data in all pixels are read out at the same time at the end of each exposure. This mechanism is called global shutter of the CCD sensor. For a CMOS sensor, the exposure and data readout are performed row by row, the data of one row read out immediately when the exposure of this row is finished. This is known as the rolling shutter mechanism of the CMOS sensor [12]–[15]. By the rolling shutter mechanism of CMOS sensor, turning on and off the LED light during a period of exposure would result in bright and dark stripes on the image captured by CMOS sensor.

2.1.2 Camera Requirement: Cameras export many properties which affect the images they capture. When a camera is used as a receiver in VLC system, the two most important properties are exposure time and film speed.

2.1.2.1 Exposure Time: The exposure duration determine how long a pixel collects photon. During exposure, the pixels accumulate charge until saturation when they are irradiated by light.

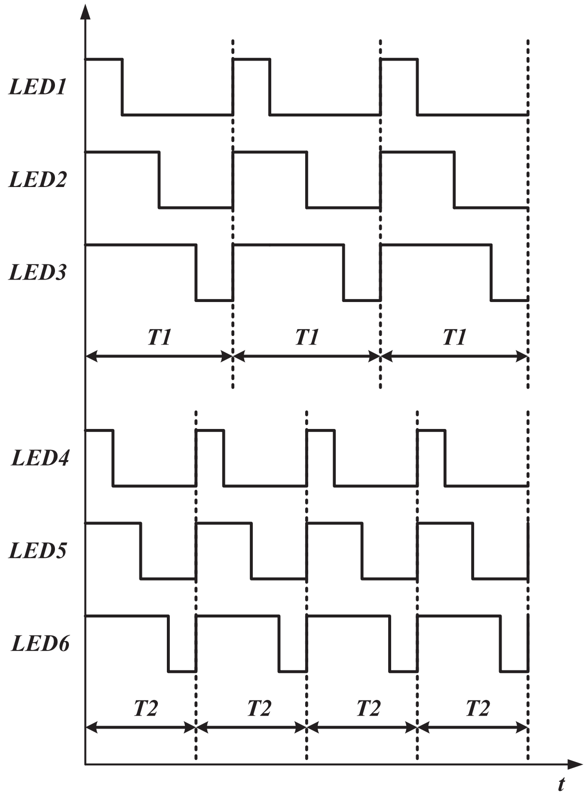

Fig. 2. The modulated scheme.

The LEDs are not only used as a transmitter, but also the light sources of the indoor environment, so the LED illumination intensity is very high, and the pixels' charge would reach saturation in a short time. When a pixel's charge reaches saturation, if irradiating it continue, the charge would overflow to the near pixel result in the charge accumulation and saturation in the near pixels. Therefore, if the exposure time is too long, the width of the bright stripes would decrease, and the reception would be affected.

2.1.2.2 Film Speed: Film speed (ISO) indicates the sensitivity of the image sensor to the light, that is, how many photons a pixel need to reach saturation. The faster film speed (higher ISO), the fewer photons a pixel need to reach saturation. It means the probability of saturating a pixel would increase in the same exposure time, and the width of bright stripes in the captured image would also increase, so that the correction of the data decoding would decrease.

2.2 LED Modulation

In this paper, a PWM method with variable frequency and duty-ratio is proposed (Fig. 2). According to the rolling shutter mechanism of CMOS sensor, the number of bright stripes on the LED project could be changed by changing the modulate frequency of LED, and the duty-ratio of bright stripes could be changed by changing the duty-ratio of PWM.

The images of different LEDs modulated by PWM with different frequency and duty-ratio are shown in Fig. 3. it can be clearly seen that, Fig. 3(a)–(c) or (d) and (e) are modulated with the same frequency but different duty-ratio. At the same distance between LED and camera, the number of bright stripes are the same, and the duty-ratio of bright stripes are different. In Fig. 3(a) and (d), the modulated frequency are different, and the duty-ratio are the same, so we could observe that they have the same duty-ratio of bright stripes and different number of bright stripes.

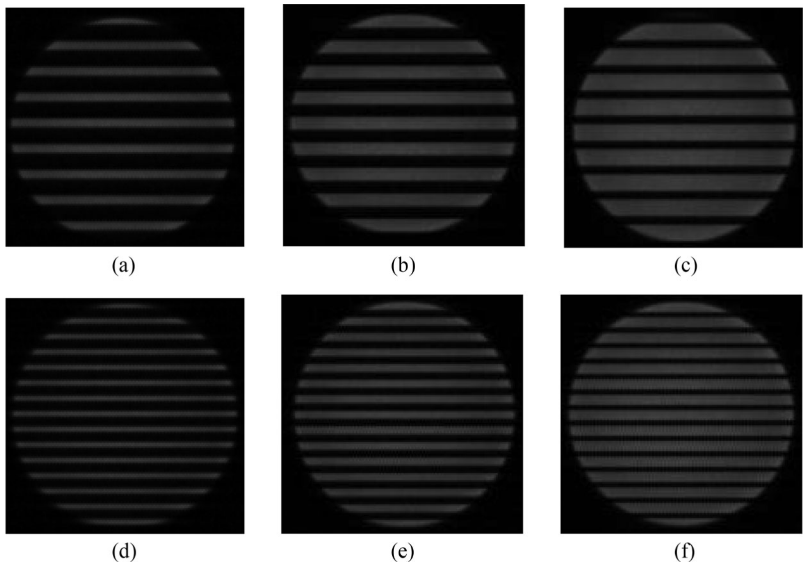

Fig. 3. Different LED images captured by CMOS sensor, (a) LED1; (b) LED2; (c) LED3; (d) LED4; (e) LED5; (f) LED6.

2.3 LED-ID Feature Extraction and Selection

As the distance between LED and camera increase, the area of the LED project on the CMOS sensor will decrease. For the same LED project, the width of the light and dark stripes will not change because of the fixed scanning frequency of the CMOS sensor. So the number of the light stripes or the dark stripes will decrease as the area of the LED project on the CMOS sensor decrease. Therefore, in this paper, we selected three features: the area of the LED project, the number of bright stripes and the duty-ratio of the bright stripe as the features of each LED, and identify different LEDs by using a classifier. The flow diagram of the LED features extraction process is shown in Fig. 4 and the LED-ID feature extraction and selection steps are as follows:

Step 1: LED project segmentation

The image sensor captures several LEDs in an image every time. To extract the features of the LED-ID, the first stuff is to segment each LED area in the captured image. The whole image is binarized at first. And then, to smooth the contour breaks narrow isthmuses of the LED projects, we do the closing operation [16]. Finally, the LED projects can be segmented one by one easily. For the convenience of the following steps, we segment the binary image, like Fig. 5(d) and (e).

Step 2: Calculate the Area of LED project

It is easy to get the radius of the LED projects (as shown in Fig. 6) which are segmented in Step 1. And the area of the LED project can be calculated according to the follow equation:

$$S = 2\pi r^2 \tag{1}$$

Step 3: Get the number of the bright stripes

To get the number of the bright stripes in each LED project, the method we proposed is to thinning the binary image we have obtained in Step1 at first (as shown in Fig. 7), and then sample the center column of pixels across the thinning image as a vector. The number of bright stripes equals the total number of elements in the vector that have a value of one.

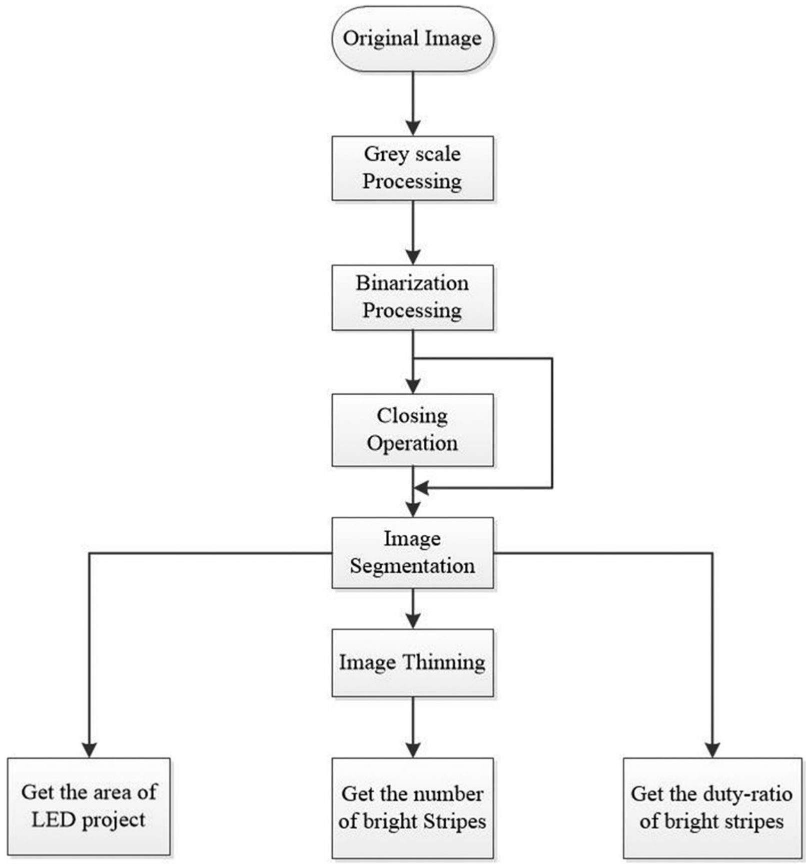

Fig. 4. Processing of LED features extraction.

Step 4: Get duty-ratio of the bright stripes

A pixel value in a binary image is either one or zero. To the binary image we have obtained in Step 1, the pixel belongs to the bright stripes when its value is one, otherwise, it belongs to the dark band or the background. We sampled the center column of pixels across the binary LED image as a vector, and the duty ratio of the bright stripes can be obtained by calculating the ratio of the number of one to the length of the vector.

After the image process proposed above, the three features of the LED project could be extracted. Considering the interference of the ambient light, when the intensity of the ambient light is too high, the contrast of the bright stripes and the dark stripes would reduce, which means some error might be occurred when we binary the image in step 1 and get the duty-ratio of the bright stripes in step 2. In our previous work in the Ref [12], we have discussed the situation like mentioned above, and we proposed a method of using the contrast limited adaptive histogram equalization (CLAHE) to enhance the contrast of the light and dark stripes when the contrast of the bright and dark stripes is too low. And the experiment demonstrated in [12] shows that the CLAHE is strong enough to enhance the contrast of the bright and dark stripes. Therefore, when the intensity of the ambient light is too high to affect the features extraction of the LED project, we could use the CLAHE before we binary the image in step 1 and reduce the interference of the ambient.

2.4 LED Recognition

2.4.1 Machine Learning: In 2.2, 6 LEDs have been modulated by 6 different frequency and duty-ratio PWM method, and the features of the LED-ID could be extracted in 2.3. The feature space is

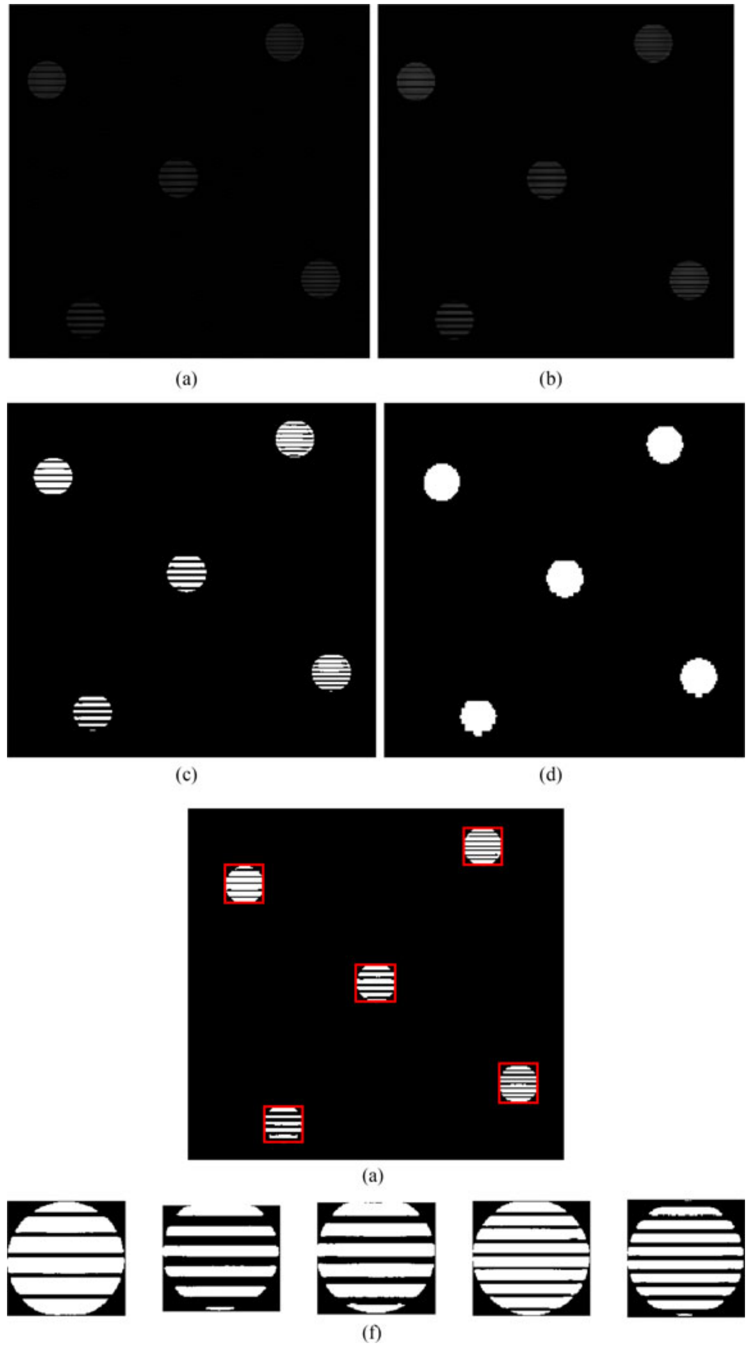

Fig. 5. The image segmentation processing; (a) original image; (b) grayscale image; (c) binary image; (d) binary image after closing operation; (e) region of interest (ROI) of the LED image; (f) segmented images.

drawn in Fig. 8, where x axis represents the number of bright stripes, y axis represents the area of the LED project, z axis represents the duty-ratio of bright stripes.

As we could see in the feature space, for two different LED-ID, they are linear separable. To achieve the recognition of LED-ID, in the machine learning filed, there are two typical linear classifier can be used in this case, Fisher classifier and Linear Support Vector Machine (SVM).

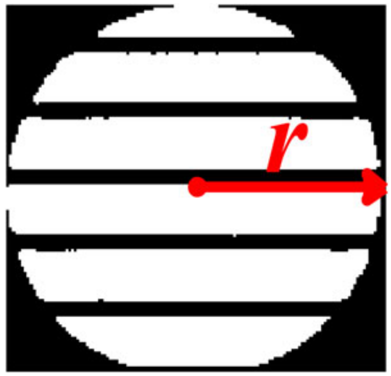

Fig. 6. The radius of the LED project.

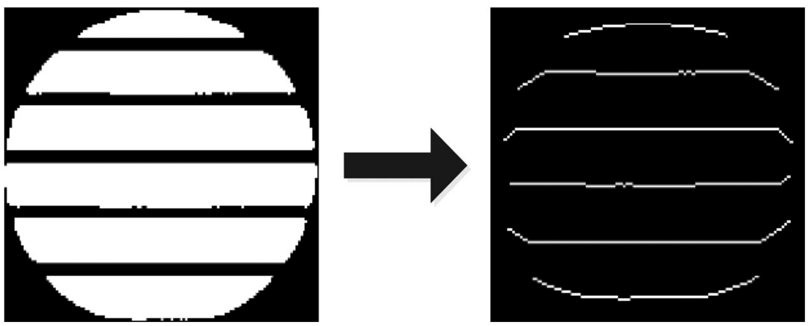

Fig. 7. Image thinning process.

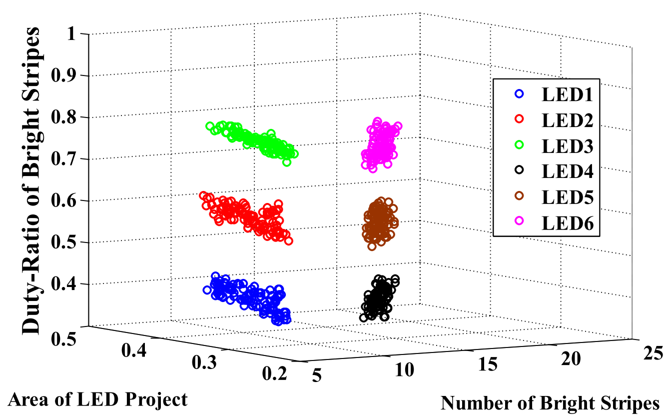

Fig. 8. The feature space of the LED.

In this paper, we introduce two typical linear classifiers in the case of two-class classification problem. For the multiple case, there exists different algorithms to multiclass problem as "One Against All" (OAA) and "One Against One" (OAO), which is descripted detailedly in [17].

2.4.2 Fisher Classifier: Fisher discriminant analysis (FDA) is a typical method in linear discriminant analysis (LDA). The basic idea of FDA is to find a projection vector ω that different classes would be separated as far as possible after projecting on to ω, and the same class would be as close as possible after projecting onto ω [18]. We briefly introduce the mathematical principles of FDA as follows:

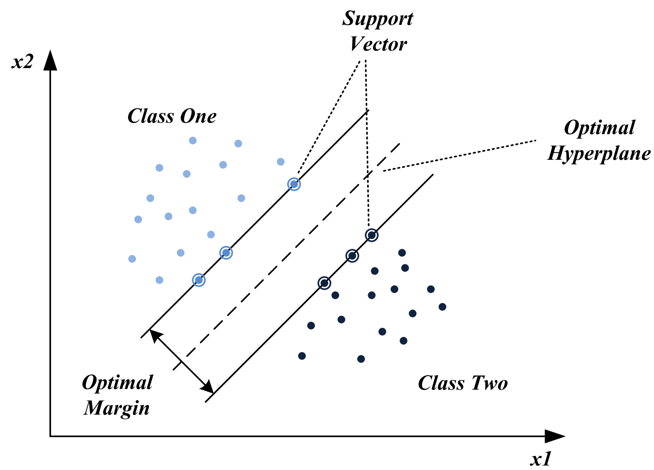

Fig. 9. An example of a linearly separable two-class problem with two possible linear classifiers.

Define Fisher linear discriminant function:

$$J_F(\omega) = \frac{|\tilde{m}_1 - \tilde{m}_2|^2}{\tilde{S}_1^2 + \tilde{S}_2^2} \tag{2}$$

Where $m_i(i = 1, 2)$ is the mean of the transformed sample vector:

$$\tilde{m}_i = \frac{1}{n} \sum_{y_k \in Y_i} y_k, \;\; i = 1, 2 \tag{3}$$

where y_k is the vector after projecting onto $\boldsymbol{\omega}$. And $Y_i = \{y_1, y_2, \ldots, y_k\}$ is the training sample after projecting onto $\boldsymbol{\omega}$.

The within-class scatter S_i^2 is defined as:

$$\tilde{S}_i^2 = \sum_{y_k \in Y_i} (y_k - \tilde{m}_i)^2 \tag{4}$$

Where $\boldsymbol{\omega^*}$ is the solution of the maximum value of $J_F(\boldsymbol{\omega})$, and the final ω^* is achieved by:

$$\boldsymbol{\omega}^* = S_{\boldsymbol{\omega}}^{-1}(m_1 - m_2) \tag{5}$$

Here $S_{\boldsymbol{\omega}}$ is the sum of each class's covariance matrix $S_i(i = 1, 2)$ and $m_i(i = 1, 2)$ denotes the mean value class i.

$$S_i^2 = \sum_{x_k \in X_i} (x_k - m_i)^2 \tag{6}$$

where x_k is the feature vector. And $X_i = \{x_1, x_2, \ldots, x_k\}$ is the training sample.

When the $\boldsymbol{\omega}^*$ is achieved, the feature space is constructed and the high dimensional spectra can be transformed to the low dimensional space to achieve dimensionality reduction.

2.4.3 Linear Support Vector Machine: Linear Support Vector Machine (SVM) is different from the FDA, it designs an optimal hyperplane (such as in Fig. 9) in the feature space to separate different classes of samples [17]. For a two class case, Let x_i, $i = 1, 2, \ldots, N$, (N $=$ 3 in our case) be the feature vectors of the training set $\boldsymbol{x}$. These belong to either of two classes, ω_1, ω_2, which are linearly separable. The goal, once more, is to find a hyperplane:

$$f(\boldsymbol{x}) = \boldsymbol{\omega}^T \boldsymbol{x} + b \tag{7}$$

that classifies correctly all the training vectors. Where $\boldsymbol{\omega}$ determines the direction of hyperplane, which has the same dimension of $\boldsymbol{x}$, $\boldsymbol{\omega}^T$ represents the transpose of $\boldsymbol{\omega}$,and b determines the exact

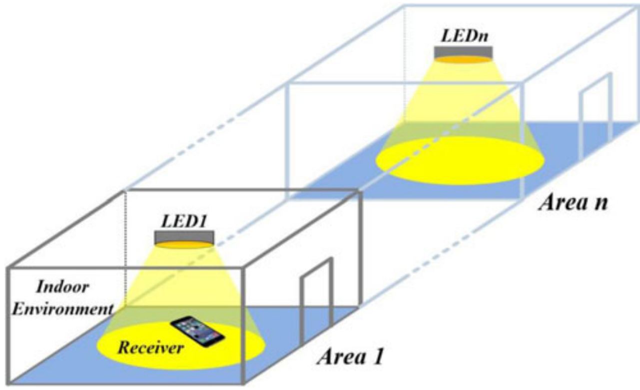

Fig. 10. Proximity based positioning method.

position of the hyperplane in space. Such a hyperplane is not unique, we define the geometrical margin:

$$z = \frac{|f(\boldsymbol{x})|}{\boldsymbol{\omega}} \tag{8}$$

Which represent the geometrical distance from the samples to the hyperplane. To get the optimal hyperplane, we aim to maximize z. Since the value of $|f(\boldsymbol{x})|$ can be changed by scaling $\boldsymbol{\omega}$ and b, when we make it equal to 1, the solution we have to find is to search the maximum $\frac{1}{\|\omega\|}$.

To solve this problem, it is easier to use the Lagrange multiplier. The problem comes to solve:

$$f(x) = \sum_{i=1}^{n} y_i \alpha_i \langle \boldsymbol{x}, \boldsymbol{x_i} \rangle + b \tag{9}$$

Where y_i is the corresponding class indicator of $\boldsymbol{x_i}$ ($+1$ for ω_1,-1 for,ω_2), α_i is the Lagrange multiplier, $\langle <, > \rangle$ represent the vector inner product.

2.5 Proximity Based Positioning

The proximity based positioning is the simplest location method, which cannot give the accuracy positions but only approximate location information [19]. In this paper, each LED illuminate unique identification (ID) data associated with the location information, which is stored in a databased. Once the LED-ID is recognized, the receiver device will look up the position information associated with the received ID in the databased. And the approximate position of the receiver can be determined (Fig. 10).

3. Experiment and Analysis

The feasibility of the proposed scheme is demonstrated experimentally, and the whole system architecture is described in Fig. 10. In this system, the LED downlight, which shows a good performance in our prior work in [12], is used as the transmitter. The modulated data is stored in a micro-controller unit (MCU) which is embedded in the LED. And each MCU controls LED driver to drive LED luminaire emitting the optical data. In the receiver subsystem, an industrial camera (XWJG, MV-U300) is used to capture the image data, and then the captured image is processed by using the MATLAB software in computer with the proposed method. All the key system parameters adopted are provided in Table 1.

TABLE 1
Parameter of the Experiment

Parameter	Value
The focal length/mm	3
The resolution of the camera	2048×1536
The exposure time of the camera/ms	0.1
The ISO of the camera	100
The pixel size of the camera/μs	3.2×3.2
The diameter of the LED downlight/cm	15
The Power of each LED/W	3
Indoor space unit size (L $\times$ W $\times$ H)/m^3	$1.7 \times 0.8 \times 2$
Current of each LED/A	0.1
Voltage of each LED/V	30

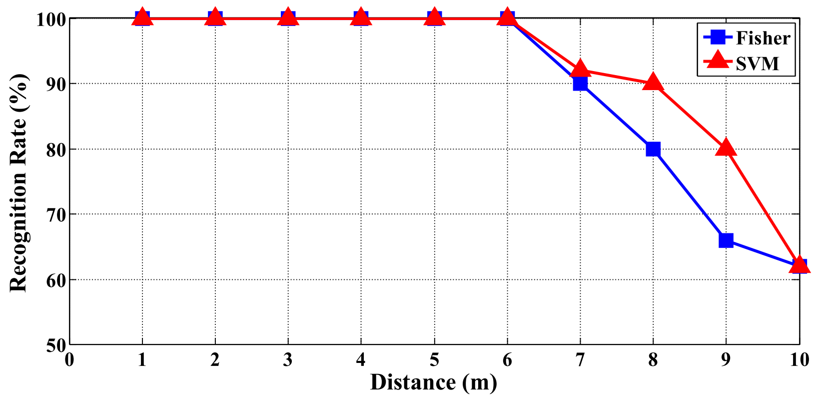

Fig. 11. The recognition rate at different distance.

3.1 Distance and Recognition Rate Analysis

As the distance between the LED and camera increase, received intensity at the CMOS sensor drops due to line of sight path loss, the area of the LED project onto the image sensor decrease, and the number of the bright and dark stripes of each LED project would also decrease. Although the width of the bright and dark stripes would not change, but as the received intensity drops, the ability of the detection of the bright and dark stripes would also be weak. These factors reduce the ability to recognize the LED-ID.

To explore the distance between the camera and LED influence on LED-ID recognition rate, we modulated the LED with PWM modulation with frequency of 1 kHz and duty-ratio of 50%. Respectively, at a distance of 1 $\sim$ 10 m, we acquired 10000 images at each position, and test the recognition rate with two trained classifiers mentioned in 2.4.

As we can see in Fig. 11, with the increase of distance between transmitter and camera, the ability of LED-ID recognition would decrease. In this system, the recognition rate performs better until 6 m whether using Fisher classifier or SVM. This performance is suitable for most of the indoor environment.

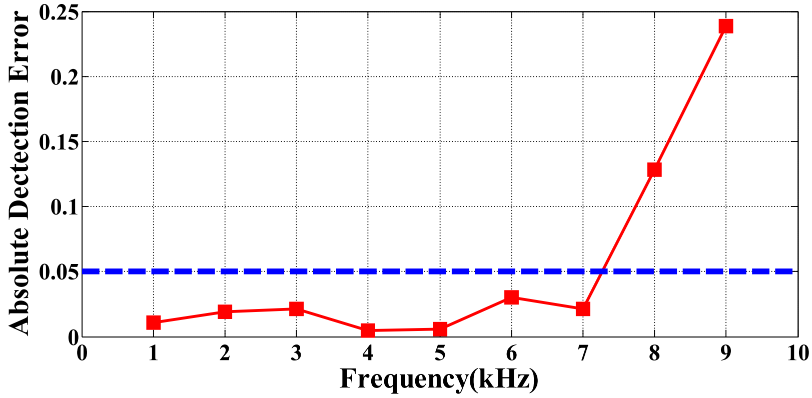

Fig. 12. The absolute value of the bright stripe's duty-ratio detection error at different frequency.

3.2 Frequency and Bright Stripe's Duty-Ratio Detection Error Analysis

When the modulation frequency of the LED increases, the time for LED to turn on or off decreases, the width of the light and dark stripes in the image will also decrease, which cause greater detection error for the duty ratio of the bright stripes. As we could know in Section 2.3, if we could extract the duty ratio of the bright stripes correctly, we could get the number of bright stripes correctly. However, the accurate identification of the number of bright stripes does not guarantee that we obtain accurate duty ratio of the bright stripes. Therefore, in the case of duty-ratio of 50%, we sweep the frequency from 1 to 10 kHz in 1 kHz steps and evaluates the ability of duty-ratio of bright stripes detection. The relationship between the transmit frequency and the absolute value of the bright stripe's duty-ratio detection error is shown in Fig. 12.

As the Fig. 12 shows, when the transmit frequency is less than 7 kHz, the absolute value of the bright stripe's duty-ratio detection error is less than 0.05. And the absolute value of the bright stripe's duty-ratio detection error is much larger than 0.05 if the frequency is greater than 7 kHz, which may cause different LED-ID become linear inseparable in the feature space, and the ability of the recognition would fall. Since the human eyes require the frequency of LED greater than 100 Hz [20], [21], the proposed method could support the bandwidth from 0.1 kHz to 7 kHz.

3.3 Bright Stripe's Duty-Ratio and Bright Stripe's Duty-Ratio Detection Error Analysis

In experiment 3.2, it has been confirmed that the absolute value of the bright stripe's duty-ratio detection error is less than 0.05 when the modulation frequency is less than 7 kHz. Therefore, in this section, with the frequency is 1 kHz, we selected the duty-ratio of bright stripes from 0.1 to 0.9 in 0.1 steps, and test the absolute ratio detection error in different duty-ratio of bright stripes.

As the Fig. 13 shows, with the duty-ratio of PWM from $0.1 \sim 0.9$, the absolute value of the bright stripe's duty-ratio detection error is 0.04 at the maximum and 0.007 at the minimum, all of which are below 0.05. That means the detection error of the bright stripe's duty-ratio would not affect the linear separability of different LED-ID in the feature space. It is indicated that each modulation frequency could offer 9 channels with 9 different duty-ratio.

3.4 Frequency Resolution and LED-ID Recognition Analysis

At the same distance, different frequencies will cause the number of bright stripes on the LED image to change, but if the frequency interval is too small, the number of bright stripes may not change, which will affect the classifier's training and recognition. Therefore, this section tests the impact of different frequency intervals on the LED-ID recognition rate, the experimental results are as follows:

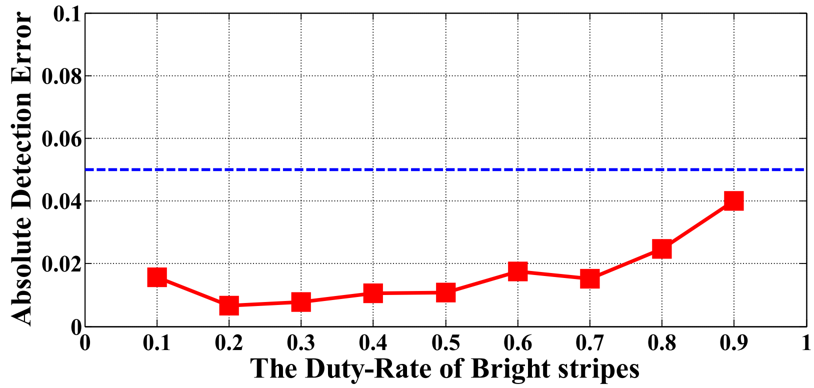

Fig. 13. The absolute value of the bright stripe's duty-ratio detection error at different duty-ratio of bright stripes.

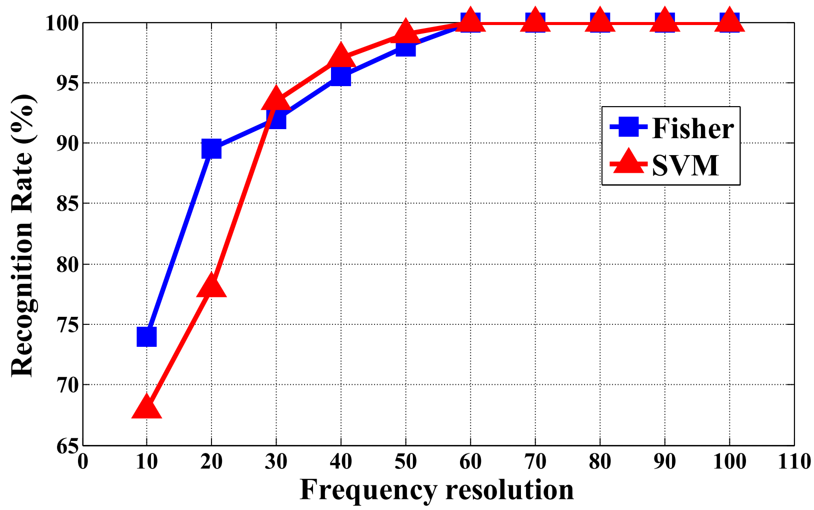

Fig. 14. The recognition rate with different frequency resolution.

As can be seen from the Fig. 14, when the frequency resolution is too small, the probability of incorrect recognition of LED-ID between adjacent frequencies is greatly increased. When the frequency interval exceeds 60 Hz, both of recognition rate of the Fisher classifier and linear SVM are up to 100%. Thus, to ensure the high robustness, the proposed method should have a frequency resolution of at least 60 Hz.

Through experiments 3.2 $\sim$ 3.4, we can know that the proposed scheme of LED recognition, with modulation bandwidth of 0.1 $\sim$ 7 kHz, frequency resolution of 60 Hz and 9 different duty-ratio in each frequency, could offer roughly $\frac{7000-100}{60} \times 9 = 1035$ unique LED-ID. It is enough to the large-scale indoor application. In addition, the camera used in our experiment has only 3 million pixels, and now the mobile phone camera pixels are generally 5 million or more, with the development of camera technology, the proposed method would provide more channels for LED recognition.

3.5 Experimental Test

In this paper, we use the proximity method to get the approximate position of the terminal. And it only needs one LED to determine the position of the receiver. But our LED-ID detection and recognition method could also be applied in many other image-sensor based VLP algorithm, and

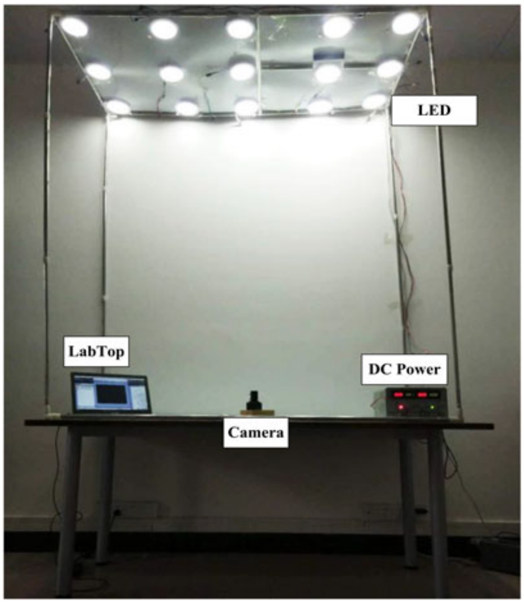

Fig. 15. Experimental platform of LED recognition.

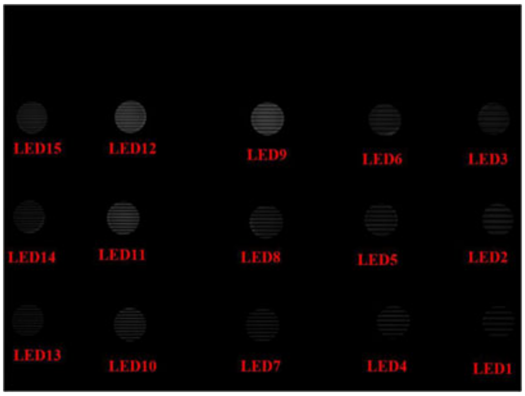

Fig. 16. The image captured by industrial camera.

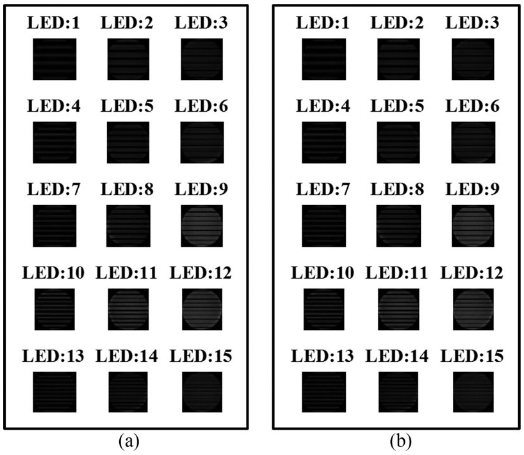

Fig. 17. The recognition result of (a) Fisher classifier; (b) SVM.

there are always more than one LED in the view of the camera. Therefore, in order to verify the practicality of the proposed LED-ID detection and recognition scheme, we set up a 1.7 m $\times$ 0.8 m $\times$ 2 m experimental platform (show in Fig. 15), which arranged 15 LED lamps, and each LED is encoded by the method we proposed. The LED images captured by the industrial camera used in experiments 3.1 $\sim$ 3.4 is shown in the Fig. 16, where the red words are the real serial numbers of each LED. The LED-ID are identified by Fisher and SVM classifiers. The recognition results are shown in Fig. 17(a) and (b), we can see that both classifiers can recognize the LED-ID well.

4. Conclusion

In this paper, a LED-ID detection and recognition method based on visible light positioning using proximity method is proposed in order to make up for the lack of research on LED-ID identification in the existing VLP reports. In order to provide a high robustness and widely used LED-ID identification scheme, we regard the LED-ID identification problem as a classify problem in the machine learning filed. A variable frequency and duty-ratio PWM method is employed to create different features for different LEDs. So that the features of different LED-ID is linear separable in the feature space, and a Fisher classifier or a linear SVM can be used to identify the LED-ID once the feature extraction and selection of LED-ID is achieved by the proposed image processing method. In addition, aim to improve the practicality of the system, a proximity based positioning method is used in the article since the approximate location information of the terminal can be obtained once the LED-ID is recognized correctly.

As the experiment result shows, the proposed scheme could offer roughly 1035 unique LED-ID for an image-sensor-based VLP system with 100% LED-ID recognition rate, and the maximum distance between transmitter and terminal can reach to 6 m. Furthermore, with the development of the camera technology, the proposed method would offer more unique LED-ID and the maximum distance between transmitter and terminal would also increase. Therefore, this scheme can be used in the large-scale image sensor based VLP system, and apply in variety of large-scale indoor applications.

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