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Modified Multi-target Recognition Based on CamCom

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Abstract: Targets recognition methods based on Camera Communication (CamCom) face these challenges: low communication bandwidth, high Bit Error Rate (BER) due to bad frames and long response time. In this paper, a modified recognition method based on CamCom is proposed. In the method, Light-Emitting Diode (LED) which embedded in targets emits ON-OFF keying periodic light signals, basic image processes segment and capture the signal from sequential images, the features of signals are extracted by Fast Fourier Transform (FFT), and then Support Vector Machine (SVM) is used to classify each signal and to identify the corresponding target. Experiments showed that compared with CamCom based or vision based recognition methods, this method can locate and recognize targets fast and accurately, has short response time to new targets and can endure occasional error data.

Key Words: Vision recognition, Pattern recognition, Camera Communication, CamCom, Optical Camera Communication, OCC, Computer Vision

1 Introduction

Visual based multi-target recognition, which is a key technology for robotics, automation, positioning, navigation, visual surveillance, has tremendous prospects in application.

Conventional multi-target recognition methods usually use features of targets appearance [1-6]. However, these methods do not perform as well when targets have no distinctive features, targets are small, or complicated background interference the target appearance. Furthermore, these approaches have high computational cost.

CamCom or Optical Camera Communication (OCC) [7, 8] is a method which uses image sensors to receive LED modulated signals, and uses the signal to track, recognize and communicate [9-11]. CamCom would be rapidly gaining attention due to the popularity of camera embedded devices. An indoor positioning system which obtains the user's position based on CamCom is proposed in [12]. An Advertisement Serving (AS) system is implemented which uses CamCom to receive the link of the advertisement. CamCom based Intelligent Traffic System (ITS) [13-15] let vehicles precisely detect the relative position, distance and states of other vehicles or traffic lights.

However, some disadvantages of CamCom limit its applications in target recognition. Due to consumer image sensors usually have frame rate of tens of frames per second (normally 30fps or 60fps), the bandwidth of CamCom is low normally several bits per second. The CamCom system would spend long time to transmit the identification data. Error rate of the data would increase as the image quality decreased. Due to most CamCom communication systems are unidirectional, error bit in the signal would let the receiver wait another repeated signal again to get complete data. These defects would decrease the response time significantly.

Considerable research has been conducted to handle the disadvantages [16-18]. Multiple-Input Multiple-Output (MIMO) [19, 20] is proposed to use spatially light source to enhance the capacity and robustness of CamCom. However, this system needs high resolution cameras and massive computation requirement. High frame rate camera [21] or specialized image sensors [22-24] are deployed in some situations. However, it would increase the hardware cost and limit the applications.

In this paper, a method based on CamCom for multi-object recognition is proposed.

First, a unique identification data is coded in ON-OFF keying periodic light signals and emitted by LED. Liquid Crystal Display (LCD) was used to simulate the light signal in our experiments. Second, basic image process algorithms including image difference is used to segment the signal. Third, a sliding window is used to capture fragments from the signal. FFT is used to extract the features from fragments due to the signal is periodic, and a simple classification method SVM is used to classify the features, than the corresponding target can be identified. Due to the sliding window can use previous data the receiver doesn't have to wait for headers of signals and can recognize the target in each frame. Furthermore, the method has low computational cost.

Experiments showed that this method can locate and recognize the targets with high response speed and accuracy. Low video quality or occasional error data have no effection on its performance. Efficient algorithms of this method make it be suitable for real-time applications.

The framework of this method including coding algorithms, image processing algorithms, FFT feature extraction approach, and SVM based recognition algorithms are introduced in Section 2. Then the experimental results are shown in Section 3. The conclusion is written in Section 4.

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2 Recognition Method

This section introduces the signal coding scheme, image process approaches, FFT based feature extraction algorithms and SVM based classifier.

2.1 System Structure

The structure of the tracking system is shown in Fig. 1.

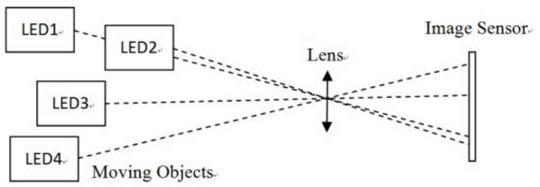


Fig. 1: The Structure Diagram

Each individual target is embedded an LED emitter to emit periodic light signals. The LED can also be replaced by LCD or other illuminative components. A camera captures the signal as sequential images which would be used to tracking and recognize each target.

2.2 Signal Coding

There are many coding schemes in communication systems. Due to LEDs have two stable states, on and off, the received and normalized signal are square waves. The combination of different frequency square waves is used to generate the signals. The Fourier expansion of square wave is shown in Eq. (1), where E is the strength of the signal; ω_0 is the frequency of each square wave. It demonstrates that different frequency square waves can be extracted by Fourier expansion.

$$f(t) = \frac{2E}{\pi} \sum_{i=0}^{n} \frac{1}{2i+1} \sin(2i+1)\omega_0 t \tag{1}$$

Three square waves were combined in the signals, and the periods of the square waves were 50ms, 100ms, and 150ms. Compared with the sample interval of the camera in experiments which was 33ms, the shortest period of time of square waves was a little longer, due to it can decrease bad frames effectively which mentioned in [26]. There are 4 ways to combine these 3 square waves in 200ms which are shown in Table 1.

Table 1: 4 Combinations of 3 Square Waves

Number	Combinations
1	50ms*4
2	100ms*2
3	150ms+50ms
4	100ms+50ms*2

2.3 Signal Segmentation

In the beginning, conventional and slight computation burden color filter algorithm is used to eliminate the interference.

The distance between color vector $\mathbf{z}$ of the LED and color vector $\mathbf{a}$ of each pixel can be measured by Eq. (2). And if the inequation $D(\mathbf{z},\mathbf{a}) \geq D_0$ is satisfied, which pixel is irrelative interfere in the image is confirmed. D_0 is the threshold value of color distance.

$$D(\mathbf{z},\mathbf{a}) = \|\mathbf{z}-\mathbf{a}\| = \left[(z-a)^T (z-a)\right]^{\frac{1}{2}} \tag{2}$$

The modified difference algorithm is expressed in Eq. (3) which is used to extract the LED from images. Where $D_{ij}(x,y)$ is the pixel in differential images.

$$D_{ij}(x,y) = \begin{cases} 0, & \left|f(x,y,t_i) - f(x,y,t_j)\right| < T \\ \left|f(x,y,t_i) - f(x,y,t_j)\right|, & else \end{cases} \tag{3}$$

The erosion operation is used to eliminate residual noise in the processed images.

If the LED state doesn't change between two adjacent images, difference image algorithm can't segment the LED directly. To solve this situation, an attenuation function is proposed to use several previous difference images to remember the LED position. The function is shown in Eq. (4), where $P_k(x,y)$ is the position image; $D_{k-i}(x,y)$ is the i^{th} previous N differential images.

$$P_k(x,y) = \sum_{i=0}^{N} e^{-\alpha \cdot i} \cdot D_{k-i}(x,y) \tag{4}$$

Image thresholding segmentation method is used to generate binary images of the position image, Blob analysis is used to segment and locate each connected area and obtain the number of LEDs in the image.

2.4 Signal Feature Extraction

A normalization process is proposed to normalize each LED signals in images, and the expressions of the functions are shown in Eq. (5), (6), and (7).

$$V_m(x,y) = \frac{1}{n} \sum_{i=1}^{n} v_i(x,y) \tag{5}$$

$$T_i = \frac{1}{n} \sum_{i=1}^{N} V_i(x,y) \tag{6}$$

$$S_i = \begin{cases} 1, & V_m(x,y) \geq T_i \\ 0, & V_m(x,y) < T_i \end{cases} \tag{7}$$

Where $V_m(x,y)$ is the mean gray value of the LED area in m^{th} image; $V_i(x,y)$ is the gray value of each pixel in the LED area; n is the number of pixels; S_i is the state of the LED in each frame; T_i is the threshold value which is the mean of previous several $V_m(x,y)$. The normalized segment can be conceptually considered a combination of several square waves as shown in Fig.2.

In order to extract the features of the signals, a sliding window is used to capture a fragment of the normalized signals. The sliding distance is one frame at each time, so the fragment can be obtained in every frame. Due to the LED emits unique periodic light signal, Fourier expansion is considered a useful approach to extract the features. The framework of Feature Extraction is shown in Fig.3.

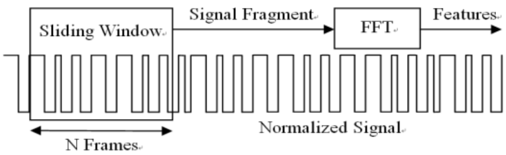


Fig. 2: The Framework of Feature Extraction

The frequency spectrum is obtained by FFT, the top N maximum values of the spectrum and their frequencies are used as features of fragments. The expression of the obtained feature is shown in Eq. (8). Where f_i is the frequency; m_i is its corresponding value. The features X_i would be used to train SVMs which are used to classify other signals.

$$X_i = [m_1, m_2, m_3, \cdots, m_N, f_1, f_2, f_3, \cdots, f_N] \tag{8}$$

2.5 SVM Based Training and Recognition

In our work, three binary-class linear SVMs were used to classify four targets, the framework of the SVMs is shown in Fig.3.

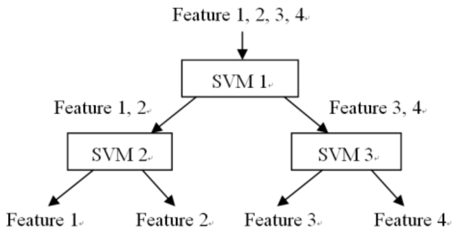


Fig. 3: The Framework of SVMs

The first SVM was used to classify the features to two parts, and the second and third SVMs are used to classify each specific feature. The training process is the same as classifying process, feature 1, 2 and feature 3, 4 are labeled as two different categories to train SVM1, and then the two parts of the features are labeled again and trained other two SVMs.

There are three parameters which have significant effect on the performance of SVMs.

First, the number of the top maximum values of the FFT results, N. There wouldn't be enough features to distinguish each signals if N is small. On the contrary, too many features would increase dimension of the hyperplanes in SVM, eliminate the weight of principal features and at the same time increase the computational requirement.

Second, the length of the sliding window. The length of sliding window decides how many sampling points in a fragment. If the sliding window is too long, it would increase the recognition time when a new target appears as well increase the computational burden. The FFT can't extract enough features of each signal if the length is short.

Third, the number of training samples. If there are too many samples, they can cause overfitting of the hyperplanes in SVM. On the contrary, small sample number would cause inaccurate hyperplanes.

The appropriate parameters would be obtained by experiments and analyzed in Section 3.

2.6 Voting Counter

A voting strategy is proposed to use current and several previous recognition results to eliminate the occasional misrecognition. The framework of the Voting Counter is shown in Fig.4.

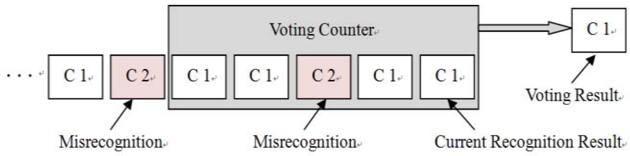


Fig. 4: Vote Counter

If more than half of the total results are the same, the voting counter will output the result. Eq. (9) shows the SVM recognition accuracy r vs. the accuracy after using voting strategy P_N. Where N is the number of total results; $P_{i/N}$ is the probability of each situation.

$$\begin{aligned} P_N &= \sum_{i=(N-1)/2}^{N} P_{i/N} \\ &= \sum_{i=(N-1)/2}^{N} \frac{N!}{i!\cdot(N-i)!} \cdot r^i (1-r)^{N-i} \end{aligned} \tag{9}$$

The plot of Eq. (9) when $N = 3,5,7$ is shown in Fig.5, when $r > 0.95$, the results of $N = 5,7$ both can reduce the misrecognition accuracy to less than 1%. Consider the computational burden, $N = 5$ is appropriate.

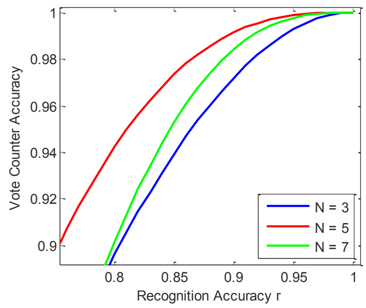


Fig. 5: The SVMs accuracy vs. Voting Counter accuracy for different N

3 Experiments

3.1 Hardware Introduction

In our work, an LCD display was used to replace the LED to emit light signals. There are four moving targets in sequential images. The program can also simulate targets out of the field, target missing, targets moving and new targets.

The experiment configurations are shown in Table 2.

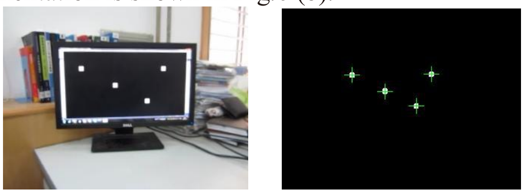
Table 2: Experiment Configurations

Name	Parameter
LED Model	DELL E2011H
LCD Size	20 inches
Screen Resolution	1600*900 pixels
Refresh Rate	60 Hz
Camera Model	Canon IXUS 115HS
Image Resolution	320*240 pixels

Frames per Second	30 fps
Image Type	Color Image

3.2 Signal Segmentation and Recognition

One of the original frames is shown in Fig.6 (a), the result of segmentation is shown in Fig.6 (b).



(a) (b)

Fig. 6: (a) Original sequential image and (b) Segmented LED position

The approach mention in 2.5 is used to extract and normalize the signal. The four normalized signals are shown in Fig.7. Due to the extracted signal was consecutive which is shown in Fig.7, the approach can extract the signal correctly.

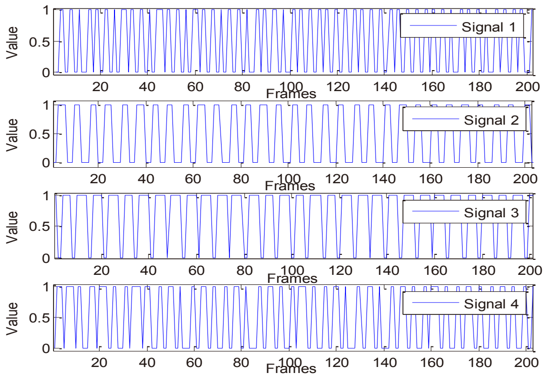


Fig. 7: Extracted and normalized signals

Fourier expansion results of the four signals are shown in Fig.8, the result illustrated that the differences between features of signals were observable. The top N maximum values and the corresponding frequencies were used to be considered as features of each signal. The red asterisks in each result were the top N maximum points.

The extracted features are used to train binary-class linear SVMs, and other signals were used to test the classification accuracy of the SVMs.

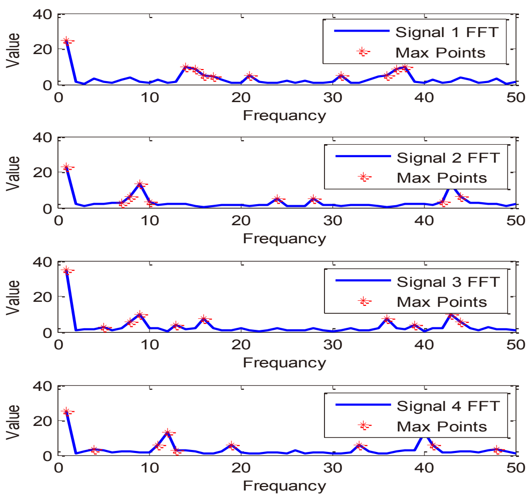


Fig. 8: The FFT result of each signal and the top N maximum values

3.3 Performance analysis

In the experiments, three parameters in this method including the number of samples, the maximum point numbers and the length of the sliding window have significant effection on the performance. Different parameters in this method were used to train the SVMs and other 1600 fragments were used to test the performance of each combination and the result was analyzed. The voting counter wasn't added in this test.

Recognition accuracy vs. sample numbers for different max point numbers is shown in Fig.9, the length of the sliding window was 25. The result illustrated that 5 maximum points was not necessary and the accuracy was slightly decrease compared with 3 and 4 maximum points, 2, 3 and 4 maximum points was appropriate. Increasing the sample number alone couldn't increase the accuracy effectively when the sample number is beyond 30.

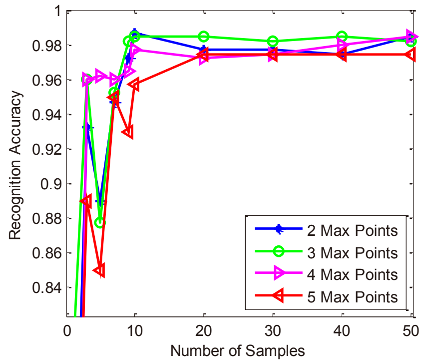


Fig. 9: Recognition accuracy vs. sample numbers for different max point numbers

Recognition accuracy vs. length of sliding window in different sample numbers is shown in Fig.10, the number of maximum points was 4, from the figure, the accuracy decreased significantly near the length of 30 no matter how many samples trained the SVMs. The result illustrated that the length of sliding window should avoid the decline near the 30 points long, 20 points long sliding window was appropriate for these signals, 40 or longer than 40 points was all right but not necessary.

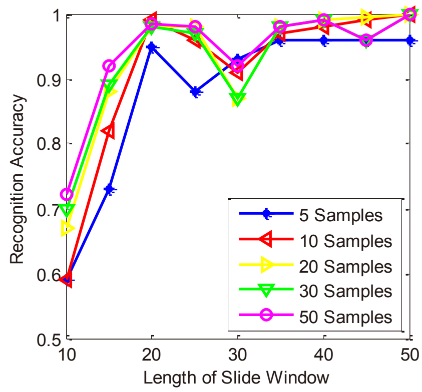


Fig. 10: Recognition accuracy vs. length of sliding window for different sample numbers

Recognition accuracy vs. length of sliding window in different numbers of maximum points is shown in Fig.11, the sample number was 20. We can also conclude that the 3 or 4 maximum points were enough to extract the features and the length of the sliding had to avoid the decline near the 30 points long. When the sliding window was beyond 10 to 15 points, the accuracy was high enough to classify the signal, so if a new signal appears, it could be identified in 0.3 to 0.5s.

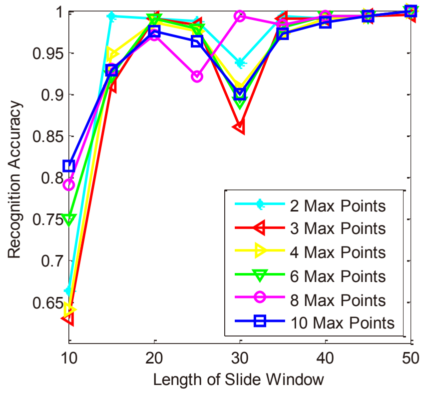


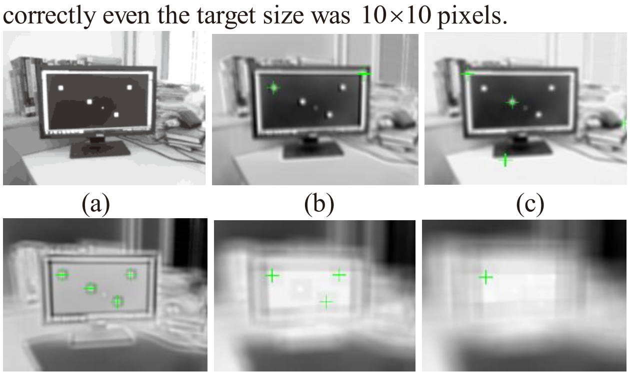
Fig. 11: Recognition accuracy vs. length of sliding window for different maximum points

From the experiment result, we can conclude that FFT and SVM were effective approaches to extract and recognize the features of the signals. However, the parameters of this method have to be tested and find the combination which has the best performance. In this specific situation, 3 or 4 maximum points and 30 or 40 samples were appropriate. More samples would lead to overfitting of the SVMs. The length of the sliding window had to avoid the 30 points long because there was a decline in recognition accuracy, 20 points long was appropriate.

3.4 Comparison

Compared with conventional template matching recognition algorithm, this method can recognize small or distant targets efficient and accuracy.

The results of template matching algorithm in different template sizes are shown in Fig.12 (b), (c), (d), (e), (f). Except Fig.12 (d), other results didn't segment the LED correctly. The result would be worse if the area of the LED become smaller, blur or the angle of the LED array changed. Due to the appearance of the targets were same, it's difficult for template matching to recognize each individual target. The results of this method in different LED areas are shown in Fig.12 (g), (h), (i), the method could still segment the target correctly even the target size was 10×10 pixels.



(a) (b) (c)

(d) (e) (f)

(g) (h) (i)

Fig. 12: The results of Template Matching and difference algorithm. (a) is the original image, and (b), (c), (d), (e), (f) are the result of 10*10, 20*20, 30*30, 40*40 and 50*50 template size matching result, and (g), (h), (i) are the result of this method in 50*50, 30*30 and 10*10 target size.

Furthermore, the time consumption of template matching is shown in Table 3. The time consumption increased as the template size enlarged. 1600 recognition tests of this method in each different parameters combination have been done, the average time consumption in each calculation including the loading time in different parameters is shown in Fig.14. The result illustrated that the increase of maximum points or sliding window length just increase the computational requirement less than 25%. And the time consumption of this method is roughly 1000 times fast than template matching.

The results illustrated that the segment performance of this method is more accurate and efficient than conventional vision based recognition method.

Table 3: Time Consumption of Template Matching

Template Size	Time Consuming
10*10 pixels	0.517s
20*20 pixels	0.658s
30*30 pixels	0.835s
40*40 pixels	1.053s
50*50 pixels	1.440s

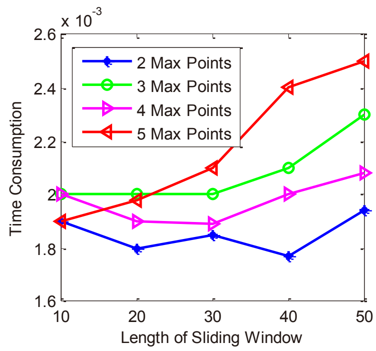


Fig. 13: Time consuming vs. length of sliding window for different sample numbers

The response time of this method is also short. Due to the fragment is captured by sliding window, the recognition result would be returned in each frame. If a new target appears, the method would output a recognition result in 8 frames in accuracy near 70%, than the accuracy would increase in each followed frame. The Voting Counter could also be used to obtain more accurate result. The response time for new targets and the accuracies are shown in Table 4. From Table 4, we can conclude that 10 or 12 frames are enough to obtain high recognition accuracy.

Table 4: Response Time for New Targets

Frames	Response Time	Accuracy	Voting Counter Accuracy
8	0.26s	0.67	0.795
10	0.33s	0.72	0.862
12	0.40s	0.85	0.973
15	0.50s	0.93	0.997
20	0.66s	0.98	0.999

Compared with this method, conventional CamCom based approaches have to receive unbroken data and return only one result in the whole process. If the received data has errors, due to the communication is unidirectional, the receiver has to wait another repeated signal again. These defects would decrease the response time significantly. A synchronized communication which proposed in [25] achieved 8 bps in 30 fps. It would take 0.5s to receive the information which can distinguish four targets. An unsynchronized CamCom communication system [26] only achieved 3 bps; it would take 1.3s to obtain the information. The time consumptions of the two methods are shown in Table 5.

Table 5: Time Consumption of other CamCom System

Name	Synchronized Communication	Unsynchronized Communication
Bandwidth	8 bps	3 bps
Time Consumption	0.5 s	1.3 s

The experiments illustrated that this method can locate and recognize the targets with high response speed and accuracy. It can recognize new targets fast. Working well in low video quality at the same time keep the algorithms being efficient that is suitable to be used in real-time applications.

4 Conclusion

A modified CamCom based multi-object location and recognition method is proposed. An identification data is coded in periodic light signal and emitted by LED array which is embedded in each individual target, basic image process algorithms are used to segment the signal, the features of signals are extracted by FFT, and then SVM is used to classify each signal and to identify corresponding target.

Compared with conventional recognition methods or CamCom based communication system, this method has advantages such as the following:

1) Due to the periodic signal emitted by LED is the only features to identify targets, appearance similarity among targets have no interference on the tracking or recognition accuracy.

2) It is robust. The size of the target can be very small, the distance between target and receiver can be far and the quality of the sequential images can be poor. Furthermore, this method can endure occasional data error.

3) The result is obtained in each frame for existing targets. The response time for new targets is short.

4) This proposed method has high operational efficiency, and it is easy to be deployed in real-time application.

In conclusion, this method can locate and recognize targets fast and accurately, has short response time to new targets and can endure occasional error data with low computational cost.

As this method can recognize only four categories in the experiments, a general code scheme and extraction method which could classify tens or hundreds targets will be developed. For the limitation of LCD refresh rate, the emitted signal didn’t follow the time scheme strictly. LED light sources will be tested in the study. Due to the image receivers are normally color camera, colored light sources may increase the accuracy and the number of categories and decrease the response time. Colored signal will be tested.

This method has potential applications in many fields as increasing popularity of camera embedded devices. For example, Indoor Navigation System (INS), advertisement serving, ITS, Automated Guided Vehicle (AGV) control system and Unmanned Ground Vehicle (UGV). How to use this method in these fields will be researched in the future.

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