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Moving Object Detection Based on Improved ViBe Algorithm

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Abstract

In this paper, an improved ViBe background subtraction algorithm is proposed for dealing with ghost problem during the process of moving object detection. The ghost areas in image can be detected based on the theory that the histogram distributions of ghost areas have similarity distribution characteristics. However, the histogram distributions of real moving objects change with the real objects moving. The influence of ghost areas on moving object detection is eliminated. The improved ViBe, the original ViBe and the Gauss mixture model are compared and analyzed, The results show that the improved ViBe can effectively eliminate ghost areas, and has high real-time.

Keywords: *moving object detecting; histogram similarity measure; ViBe; Gauss mixture model.*

1. Introduction

With the rapid development of computer science, computer vision detect technologies are used more and more extensively in many aspects of production and life. Moving object detection technology as one of the important parts of the computer vision technologies is widely used in public transport, public security and many other fields. Moving object detection technology has become a research focus recently. However, the moving object detection technology still has some shortcomings such as slow detection speed, low detection accuracy and poor environmental adaptability etc. Thus, the moving object detection technology is need in-depth study.

Many moving object detection technologies have been proposed, such as frame difference method, optical flow method and background subtraction method [1-4]. The frame difference method is the most common method. This method uses the difference value of adjacent frames in video sequences to extract moving objects. Frame difference method has good abilities of real-time characteristics and fast-calculation speed. Nevertheless, frame difference method has some shortcomings simultaneously. Such as frame difference method is particularly sensitive to environmental noise. The threshold selection of frame difference method is very strict. When the threshold selection is not appropriate, the moving objects are likely to be undetected [5-7]. Optical flow method calculates the optical flow field and detects the moving objects under the condition that the scene information is not known in advance. Optical flow method is suitable for detecting moving objects under dynamic background. However, the computation of optical flow method is huge, and it is very sensitive to noise interference [8-9].

Background subtraction method is an effective method for moving object detection, and is one of the most used methods currently [10-11]. The basic idea of background subtraction method is to establish a background mathematical model to represent background image. The difference image can be achieved to use the current frame to subtract the background image. These regions that the pixel value change is greater than

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the threshold value are selected as foreground regions in the difference image. On the contrary, these regions that the pixel value change is smaller than the threshold value are selected as background regions. The core technology of background subtraction method is to construct background model. Common background model establishment methods include single Gauss model (SGM), Gauss mixture model (GMM) and kernel density estimation etc. SGM is susceptible to noise interference in the process of establishing background model, and the modeling time is slow. GMM uses K Gauss models to establish background model, the anti-interference ability of the background model is enhanced in a certain extent. But GMM algorithm is more complex, larger time-consuming, and not suitable for real-time processing. The ViBe background subtraction algorithm is proposed by Barnich et al. [12]. The algorithm has good anti-interference ability, real-time performance and high robustness. However, the ViBe background subtraction algorithm is easy to produce ghost areas in the process of moving object detection.

An improved ViBe background subtraction algorithm for dealing with ghost area problem is proposed in this paper. The ghost areas in image are eliminated and the computational efficiency is improved. The algorithm uses the theory that the histogram of ghost areas has the similarity distribution characteristics but the distribution characteristics of real moving objects constantly change with the real objects moving to identify the ghost areas in image. The influence of ghost areas on moving object detection is eliminated. The improved ViBe, the original ViBe and the GMM are compared and analyzed.

2. ViBe Algorithm Theory

2.1. Background Model Establishment

ViBe algorithm regards moving object detection as pixel classification problem. One pixel is divided into moving object pixels or background pixels [13]. A sample set $M(x)$ is established for each pixel x in the ViBe algorithm. There are N sample values $\{p_1, p_2, p_3, \cdots, p_n\}$ in each sample set $M(x)$. p is the pixel characteristic value, e.g., RGB vector, gray values. Sample set $M(x)$ is shown as equation (1).

$$M(x) = \{p_1, p_2, p_3, \cdots, p_n\} \tag{1}$$

In general, the first frame image is used to initialize the background model. There are N sample values for each sample set, but there is only a certain value for each pixel in image. In order to solve the sample value problem in sample set, the neighborhood pixel values of each pixel is assigned to the sample set. For example, a pixel value is randomly selected from eight or twenty neighborhood of each pixel x to assign to the sample set $M(x)$. The background model establishment is completed.

2.2. Pixel Classification

$v_t(x)$ represents the pixel characteristic value of the pixel located at x in time t, the pixel characteristic value may be gray value or RGB color vector. In order to determine whether the pixel is the background pixel or the foreground pixel, a circular area $S_R(p_t(x))$ is defined that the radius is R and the center is $v_t(x)$, and a threshold T_{th} is set. $S_R(p_t(x))$ and $M(x)$ are carried intersection operator, the number NUM_c of samples that have the same sample value is obtained. If the number NUM_c is greater than the threshold T_{th}, then $v_t(x)$ will be set as the background pixels; otherwise, $v_t(x)$ will be set as the moving target pixels [14]. The whole calculation method is shown as equations (2) and (3).

$$\{S_R(p_t(x)) \cap M(x)\} = NUM_c \tag{2}$$

$$\begin{cases} NUM_C > T_{th}, & background\text{ - }pixel \\ NUM_C \le T_{th}, & foreground\text{ - }pixel \end{cases} \tag{3}$$

2.3. Background Model Update

ViBe algorithm uses conservative background updating algorithm. The pixels that are detected as moving targets in current image don't participate in background update. Considering the actual situation of camera vibration and background gradient etc., ViBe algorithm uses the following method to update the background model. Each background pixel x has $1/\Phi$ chance to update a sample in the sample set $M(x)$. In the same time, the neighborhood pixel also have $1/\Phi$ chance to update a sample in the sample set $M(x)$. The update process is to use $v_t(x)$ to replace a sample in the sample set $M(x)$ and the update process gradually spreads out. The probability of a sample existing at time t_0 and still existing at time t_1 can be written as equation (4).

$$p(t_1 - t_0) = e^{-\ln[(n-1)/n]^{(t_1-t_0)}} \tag{4}$$

It can be known from equation (4) that the probability of a sample remains in the sample set $M(x)$ is monotone decreasing. The accuracy of background pixel estimation is improved to use the above background update method.

3. Improved ViBe

ViBe algorithm principle has been described in detail in Section 2. ViBe algorithm is an efficient moving object detection algorithm. However, the original ViBe algorithm is easy to produce ghost areas during the process of moving object detection. In order to eliminate the ghost area during the process of moving object detection, an improved ViBe based on histogram similarity is proposed. The influence of ghost areas on moving object detection is eliminated.

Histogram is one of the common technologies for image analysis. Many properties of the target areas in image can be described by histogram, such as color distribution and edge gradient etc. Histogram similarity principle is according to the similarity degree that the same object has higher similarity in pixel distribution. It is widely used in image processing because of fast-calculation speed.

For existing image histograms, the method to compare the histogram similarity is to calculate the distance between two histograms. The distance can be Euclidean distance, Bhattacharyya, EMD, correlation coefficient etc. The correlation coefficient is used to compare histogram similarity in this paper.

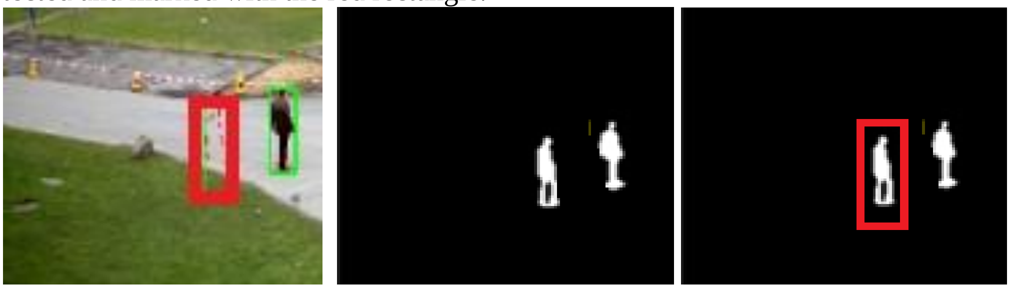
The detecting window of the former N frame images is represented by win_F_p; the detecting window of the current image is represented by win_F_c; the histogram of the former N frame images and the current image are $hist_p$ and $hist_c$, respectively. The statistical value of the *i*-th interval in histogram is $hist(i)$. Histogram similarity rate can be calculated by equation (5).

$$hm(win\_F_p, win\_F_c) = \frac{\sum_i (hist_p(i) - \overline{hist_p})(hist_c(i) - \overline{hist_c})}{\sqrt{\sum_i (hist_p(i) - \overline{hist_p})^2 \sum_i (hist_c(i) - \overline{hist_c})^2}} \tag{5}$$

It can be known from equation (5) that the range of hm is $[-1,1]$, the value of hm is larger, the similarity of $hist_p$ and $hist_c$ is higher. A threshold T_{ght} is set to determine whether the area is a ghost area. When $|hm| \ge T_{ght}$, the detecting window area is the ghost areas; when $|hm| < T_{ght}$, the detecting window area is the real target moving areas. The ghost area detecting process can be written as equation (6).

$$\begin{cases} Ghost\ area, & |hm| \geq T_{ght} \\ Target\ area, & |hm| < T_{ght} \end{cases} \tag{6}$$

Fig. 1 is to use the histogram similarity theory to detect the ghost areas. Fig. 1(a) represents that a person starts walking from the red rectangle position. The image that the person is at the red rectangle position is selected as the first frame image of the video sequence, and the image that the person is at the green rectangle position is selected as the last frame image of the video sequence. Fig. 1(b) shows the calculation results to use the original ViBe algorithm to extract the moving objects in image frames. It can be known that the left object area in Fig. 1(b) is a ghost area. Fig. 1(c) shows the results of the ghost area detection based on the histogram similarity described in this paper. The ghost area is detected and marked with the red rectangle.



(a) Original Image (b) Motion Target Detection (c) Ghost Area Detection

Figure 1. Ghost Area Detection based on Histogram Similarity

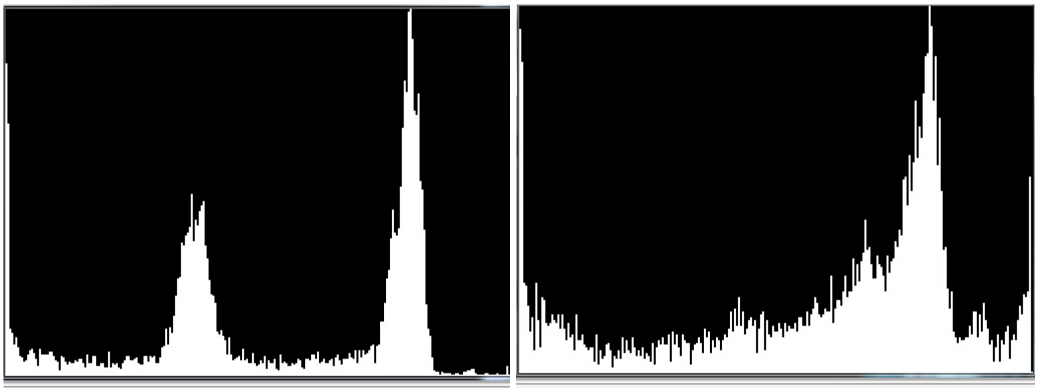
Fig. 2 represents the histogram distribution characteristics of Fig. 1. The histogram distribution characteristics are calculated according to equation (5). Fig. 2(a) is the histogram distribution characteristics of the green rectangle area at current frame. Fig. 2(b) is the overall histogram distribution characteristics of the green rectangle areas of the former 75 frame images. Fig. 2(c) is the histogram distribution characteristics of the red rectangle area at current frame image. Fig. 2(d) is the overall histogram distribution characteristics of the red rectangle areas of the former 75 frame images.

It can be seen from the comparison of Fig. 2(a) and Fig. 2(b) that the histogram similarity of the real moving objects is lower. However, the histogram similarity of Fig. 2(c) and Fig. 2(d) of the ghost area is higher. Thus, we can use the histogram similarity theory to detect ghost areas.

Tab. 1 is the calculation results of the moving object histogram similarity degree according to equation (5). The histogram similarity value of the ghost area is 0.988. However, the histogram similarity value of the real moving object area is 0.324. The ghost area has high histogram similarity value but the real moving object area has low histogram similarity value. The ghost area can accurately be detected and eliminated according to the histogram similarity value.

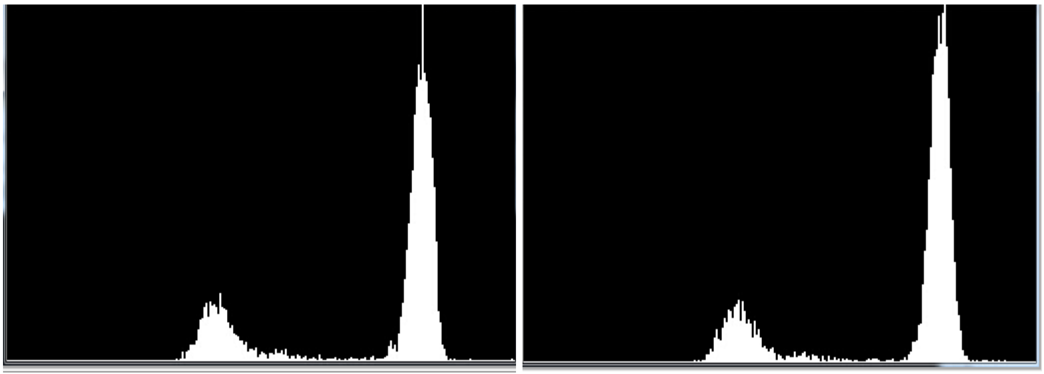
Table 1. Histogram Similarity Comparison

Object	Histogram similarity value (*hm*)	Similarity degree
Real moving object	0.324	Low
Ghost area	0.988	high



(a) Green Rectangle Histogram Distribution of Current Frame

(b) Green Rectangle Histogram Distribution of 75 Frames



(c) Red Rectangle Histogram Distribution of Current Frame

(d) Red Rectangle Histogram Distribution of 75 Frames

Figure 2. Histogram Distribution of Moving Object Detection

4. Calculation and Analysis

4.1. Comparison of Original ViBe and Improved ViBe

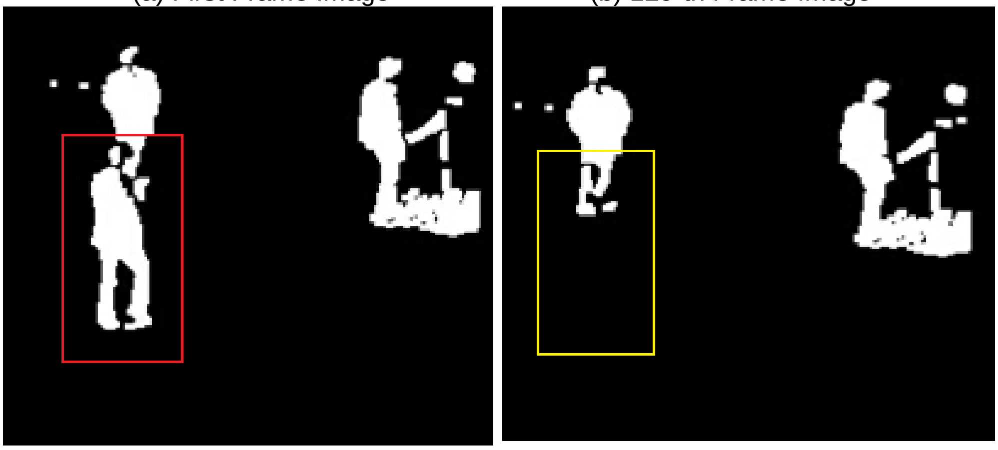
The improved ViBe and the original ViBe were applied to video sequence analysis at the same time, the comparison results are shown in Fig. 3.

Fig. 3(a) is the first frame image in the video sequence, there is a moving object in the blue rectangle in this image. Fig. 3(b) is the 129-th frame image in the video sequence. There are three different moving objects in this image. Fig. 3(c) shows the result of moving target detection based on the original ViBe. There is a ghost area in the red rectangle, because there is a moving target in the red rectangle in the first frame image. Fig. 3(d) shows the results of moving object detection based on the improved ViBe. The ghost area in the yellow rectangle has been eliminated. It can be seen from Fig. 3 that the improved ViBe is effective to eliminate the ghost area.

4.1. Efficiency Comparison

The running time is one of the important parameters in determining the algorithm efficiency, and is an important indicator of the algorithm practicality. The running time of the improved ViBe and the GMM were compared and analyzed. The computing platform is person computer, the main hardware configurations of the computer are as follow: CPU Intel Core i5 3230M, RAM 4GM DDR3, operating system Windows 7. Model parameter settings are as follow: $N = 20$, $T_{th} = 2$, $R = 2$.

(a) First Frame Image (b) 129-th Frame Image



(c) Moving Target Detection of the Original ViBe (d) Moving Target Detection of the Improved ViBe

Figure 3. Comparison of Original ViBe and Improved ViBe

Two video files testA.avi and testB.avi are used to test the performance of the improved ViBe and the GMM. The Video file parameters are shown in Tab. 2.

Table 2. Video File Parameters

filename	frames per second	Video Length (s)	Sum of frames
testA.avi	10	79	790
testB.avi	15	7	105

For the video file testA, the improved ViBe and the GMM are used to run 10 times. The running time are shown in Tab. 3. It can be known from Tab. 3 that the running time of the Improved ViBe is always less than that of the GMM for all the calculation processes.

Table 3 Running Time of textA.avi

Number of times	1	2	3	4	5	6	7	8	9	10
Improved ViBe	6.88	6.78	6.73	6.72	6.72	6.68	6.75	6.71	6.70	6.81
GMM	8.98	9.00	8.70	9.25	9.14	8.97	8.97	9.06	9.12	8.73

For the video file testB, the improved ViBe and the GMM are used to run 5 times. The running time are shown in Tab. 4. It can be known from Tab. 4 that the running time of the Improved ViBe is less than that of the GMM for all the calculation processes. Therefore, the conclusion can be got that the computational efficiency of the improved ViBe is higher than that of the GMM.

Table 4. Running Time of textB.avi

Number of times	1	2	3	4	5
Improved ViBe	188.912	183.966	178.199	178.371	178.215
GMM	290.051	287.79	287.946	288.647	287.571

From Section 4.1 and Section 4.2, it can be known that the improved ViBe algorithm can effectively eliminate ghost areas during the processes of moving object detection, and keep good real-time performance synchronously.

5. Conclusion

In this paper, an improved ViBe algorithm is proposed to deal with the ghost problem that exists in original ViBe algorithm. The improved ViBe algorithm is based on the theory that the histogram of ghost areas has the similarity distribution characteristics. However, the histogram distribution characteristics of the real moving objects change with the real target moving. The ghost areas can accurately be detected and eliminated. At the same time, the real-time of the original ViBe is reserved.

The improved ViBe and the original ViBe are compared and analyzed, and the comparison results show that the improved ViBe algorithm can effectively eliminate the ghost area during the moving target detection processes. The running time of the improved ViBe and the GMM is compared and analyzed, and the comparison results show that the running time of the improved ViBe is less than that of the GMM.

References

[1] J. B. Qu, “Variable Background Frame Difference Technology Research”, Applied Mechanics and Materials, **(2014)**, pp. 4742-4745.

[2] K. Tong, J. H. Yun and H. H. Cho, “Motion Estimation Using New Blocks Based on The Frame Difference for Frame Rate-up Conversion”, Proceedings of International Meeting on Information Display, **(2008)**.

[3] J. L. Barron, D. J. Fleet and S. S. Beauchemin, “Performance of Optical Flow Techniques”, International Journal of Computer Vision, **(1994)**, pp. 43-77.

[4] C. F. Shao and Y. Hao, J. Li, “Real-time Foreground-background Segmentation Based on Improved Codebook Model”, Image and Signal Processing (CISP), **(2010)**, pp. 269- 273.

[5] C. Z. Yu, J. Zhu and X. H. Yuan, “Video Object Detection Based on Background Subtraction”, Journal of Southeast University (Natural Science Edition), vol. 35, **(2005)**, pp. 159-161.

[6] J. Y. Zhou, X. P. Wu and C. Zhang, “A Moving Object Detection Method Based on Sliding Window Gaussian Mixture Model”, Journal of Electronics & Information Technology, vol. 35, **(2013)**, pp. 1650-1656.

[7] Y. Li, Z. X. Sun and B. Yuan, “An Improved Method for Motion Detection by Frame Difference and Background Subtraction”, Journal of Image and Graphics, vol. 14, **(2009)**, pp. 1162- 1168.

[8] D. Scharstein, S. Baker and R. Szeliski, “A Database and Evaluation Methodology for Optical Flow”, International Journal of Computer Vision, vol. 1, **(2011)**, pp. 1-31.

[9] J. Li, J. H. Lan and J. Li. “A Novel Fast Moving Target Detection Method”, Journal of Central South University (Science and Technology), vol. 44, **(2013)**, pp. 978-984.

[10] N. A. Mandellos, I. Keramitsoglou and C. T. Kiranoudis, “A Background Subtraction Algorithm for Detecting and Tracking Vehicles”, Expert Systems with Applications, vol. 38, **(2011)**, pp. 1619-1631.

[11] G. Chen, Z. Z. Yu and Q. Wen, “Improved Gaussian Mixture Model for Moving Object Detection”, Lecture Notes in Computer Science, **(2011)**, pp. 179-186.

[12] V. D. Marc and O. Barnich, "ViBE: A Powerful Random Technique to Estimate the Background in Video Sequences", IEEE International Conference on Acoustics Speech and Signal Processing-Proceedings ICASSP: Institute of Electrical and Electronics Engineer, **(2009)**.
[13] V. D. Marc and O. Barnich, "ViBe: A Disruptive Method for Background Subtraction", Contribution to collective works: Chapman and Hall/CRC, **(2014)**.
[14] V. D. Marc and O. Barnich, "ViBe: A Universal Background Subtraction Algorithm for Video Sequences", IEEE Transactions on Image Processing, vol. 20, **(2011)**, pp. 1709-1724.
[15] I. Leichter, M. Lindenbaum and E. Rivlin, "Mean Shift Tracking with Multiple Reference Color Histograms", Computer Vision and Image Understanding, vol. 114, **(2009)**, pp. 400-408.
[16] W. M. Hu, N. H. Xie and R. G. Hu. "Bin Ratio-Based Histogram Distances and Their Application to Image Classification", IEEE Transactions on Pattern Analysis and Machine Intelligence, vol. 36, **(2014)**, pp. 2338-2352.
[17] X. J. Li, J. T. Li and Y. F. He, "Method of Ghost Suppression Based on Similarity Measure", Application Research of Computers, vol. 31, **(2014)**, pp. 926-932.

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