International Core Journal of Engineering Volume 5 Issue 9, 2019
ISSN: 2414-1895 DOI: 10.6919/ICJE.201908_5(9).0001

Motion Target Detection Based on Video Image and Low Rank Sparse Matrix

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Abstract

In order to achieve accurate detection of moving objects in video images, the idea of constructing low-rank sparse matrix decomposition algorithm was used to detect moving objects in video images. The low rank sparse matrix decomposition algorithm was applied to detect moving objects in video images, and then the stability, accuracy, image extraction, restoration, error, work efficiency and other aspects of the algorithm were compared with traditional algorithms and analyzed. The results showed that the low rank sparse matrix decomposition algorithm had obvious advantages over the traditional algorithm in terms of stability. The standard deviation of the algorithm in this research was 0.011 and that of the traditional algorithm was 0.024. The algorithm in this paper also has good performance in terms of detection accuracy and error. The detection accuracy can reach 93.7%, while that of the traditional algorithm is only 79.6%. In addition, the low rank sparse matrix decomposition algorithm has no shadow on the extraction and restoration of moving images. Compared with the traditional algorithm, the computational efficiency of the algorithm in this paper is improved by 37.8%. The algorithm in this paper has no difference in the detection results of moving objects or people in video images. Based on the low rank sparse matrix decomposition algorithm, the operation of the algorithm was discussed through precise detection of moving objects in video images. The algorithm presented in this paper shows a very comprehensive outstanding result, and also shows that the efficient and normal operation of the algorithm is a comprehensive result, which requires a good operation situation of multiple. This study greatly improves the understanding of low rank sparse matrix decomposition algorithm and moving target detection.

Keywords

Algorithm; Motion target detection; Video image; Stability.

1. Introduction

Moving target detection plays an important role in following target tracking, target recognition and target behavior analysis [1]. However, how to improve the accuracy of moving target detection and restore the moving target is still a difficult problem in the field of computer vision [2]. Target detection can be divided into static target detection and dynamic target detection according to the type of input image [3]. Static target detection mainly aims at the detection of target in single frame image [4], while dynamic target detection aims at the detection of moving target in video sequence [5]. This topic mainly studies the detection of dynamic targets, that is, the detection of moving targets in video sequences [6]. In recent years, compressed sensing based on sparse representation has become a more effective way of data expression [7]. Compared with traditional subspace model learning, sparse representation has better robustness [8]. Some researchers extend the sparse representation of vectors

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to the low rank form of matrices and call it the low rank matrix recovery [9]. Low-rank matrix recovery refers to the assumption that data matrix can be expressed as the sum of low-rank matrix and sparse matrix, and the original low-rank matrix can be restored according to the optimization problem of solving the kernel norm [10]. Among them, the application of matrix reconstruction, the fast algorithm of matrix reconstruction, and the feasibility of matrix reconstruction are especially outstanding [11].

The decomposition of low-rank sparse matrix algorithm can also be called matrix reorganization. In other words, the sparse matrix and low-rank matrix are re-merged and combined [12]. Suppose that in a video image, the interconnected frame pictures have a very close relationship. The background of this picture is extremely close, and a certain number of moving targets may appear in each frame [13], such as puppies. Assuming that all the frames in this video picture are extracted and then recombined into a matrix M according to the specified requirements, this means that the matrix has low rank property, and the background in the picture can be constructed according to this background [14].

In summary, the efficiency of low rank sparse matrix decomposition algorithm was studied by detecting moving objects in video images. The results showed that the low rank sparse matrix decomposition algorithm performed very well in the accuracy and stability of moving object detection in video images. Compared with the traditional algorithm, the standard deviation of the algorithm in this paper is very low. The innovation of this paper lies in the combination of two seemingly unrelated domains, low rank sparse matrix decomposition algorithm and moving object detection. And the results were analyzed to obtain clear results, which was very important for the research of low rank sparse matrix decomposition algorithm and video image moving object. The research results still provide some guidance for future research, so it is a topic of great value.

2. Method

2.1 Establishment of low rank sparse matrix decomposition algorithm

Iterative threshold algorithm regularizes the optimization problem, and the following equation can be obtained:

$$\min \|A\| + \gamma\|E\| + \frac{1}{2\tau}\|A\|_F^2 + \frac{1}{2\tau}\|E\|_F^2 \tag{1}$$

In Equation (1), x is a relatively large positive number, which can make Equation (1) have only minor perturbations relative to the objective function. By introducing a Lagrange multiplier to eliminate the constraint conditions, the following Lagrange functions can be obtained:

$$L(A, E, Y) = \|A\| + \gamma\|E\| + \frac{1}{2\tau}\|A\|_F^2 + \frac{1}{2\tau}\|E\|_F^2 + \frac{1}{\tau}\langle Y, D - A - E\rangle \tag{2}$$

Iterative threshold algorithm is solved by alternately updating A, E and Y: fixing Y to minimized $L(A, E, Y)$, then constraining D = A + E, and updating Y. The specific implementation is as follows:

$$A_{k+1} = \operatorname{argmin} L(A, E_k, Y_k) = \operatorname{argmin} \frac{1}{\tau}\|A\| + \frac{1}{2}\left\|A - \frac{Y_k}{\tau}\right\|_F^2 \tag{3}$$

$$E_{k+1} = \operatorname{argmin} L(A_{k+1}, E, Y_k) = \operatorname{argmin} \frac{\gamma}{\tau}\|E\| + \frac{1}{2}\left\|E - \frac{Y_k}{\tau}\right\|_F^2 \tag{4}$$

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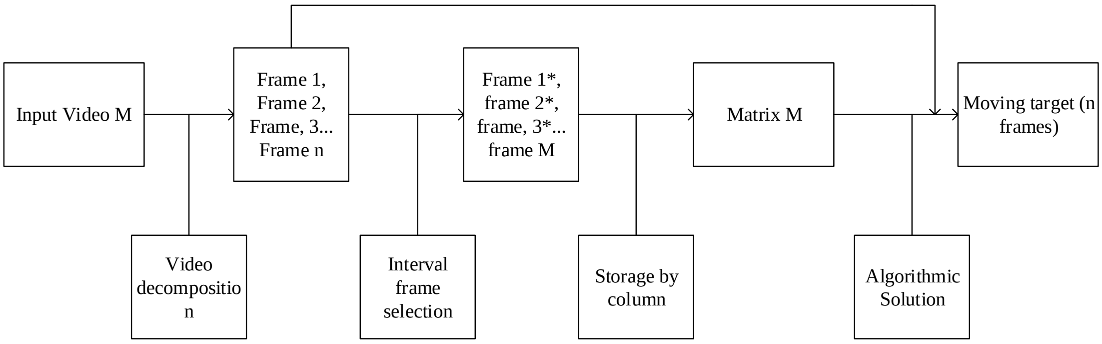

Figure. 1 Structure of moving target detection

As shown in Figure 1, according to the previous process, moving objects in video can be extracted efficiently. The first step is to extract and classify all frames in a video image (assuming a total of n frames), and then store them in a folder. Then, all n frames in the video are separated according to the same interval and m frames are selected. Finally, the moving objects in the video are extracted and solved. After obtaining the images of each frame, the specific solution is as follows: first, the image columns of m frames are stored in a matrix M. Next, an improved algorithm based on IALM is used to solve the problem, and finally the image of the moving object is obtained.

2.2 Steps of low rank sparse matrix decomposition

Step 1: Input a video V (resolution of $p \times q$) and extract all the frames in the video (frame number: n and each frame size: $p \times q$);

Step 2: For all n frames in video, m frames are selected at equal intervals.

Step 3: Each frame in the M-frame video image consists of a column vector according to certain rules. However, if the m-column vector is placed in the matrix M, the size of the matrix M is ($p \times q$)*m.

Step 4: IALM algorithm is used to decompose the matrix M to obtain the low rank matrix and the sparse matrix.

Step 5: The m frame low rank images are recovered corresponding to L recovery and the original matrix (L_1,L_2… L_m, with size of $p \times q$).

Step 6: A low-rank image is obtained by weighted fusion of m-frame low-rank images.

$$L = \frac{1}{m}\sum_{i=1}^{m} l_i \tag{5}$$

Step 7: The error image matrix $e_k = r_k - 1$ is obtained by subtracting each frame r_k (k = 1, 2., n) from the low rank image in the n frame image of the original video.

Step 8: Sett the threshold T (T is selected according to the degree of video noise damage. A large number of experiments show that the value of T in 30-40 will be better, and the value selected in this paper is also in this range). For the elements $e_k(i, j) < T$ in the image matrix e_k, if $e_k(i, j) < T$, then $e_k(i, j) = 0$.

$$e_k(i, j) = \begin{cases} 0 & e_k(i, j) < T \\ e_k(i, j) & \text{else} \end{cases} \tag{6}$$

Step 9: To mark the moving target after the operation as white and the background as black, then there are $s_K = 255 * b_k$. To recover the moving target completely, it is supposed to follow the steps below.

Step 10: Multiply b_k by r_k in the original video according to the matrix elements, $s_{K1} = r_k * b_k$.

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Step 11: Set the background color $s_{K2} = c * b_k$ of c as the pixel. It indicates that b_k will be reversed, and then the moving target is $s_K = s_{K1} + s_{K2}$. Add up the images obtained from the three layers of red, green and blue, and obtain $b_k = b_{k1} + b_{k2} + b_{k3}$. Then operate on it:

$$b_k(i, j) = \begin{cases} 1 & b_k(i, j) > 0 \\ 0 & \text{else} \end{cases} \tag{7}$$

Repeat the steps with b_k and each layer of the original image, and finally synthesize the color moving object image.

2.3 Application of low rank sparse matrix decomposition in target

In order to validate and analyze the low rank sparse matrix decomposition algorithm in this paper, four completely different video images are selected. The first one is a young man playing basketball. The background is the school basketball court, which is relatively simple with 63 frames. The second one is a grandmother shopping in the supermarket, whose background will be affected by light and there is a total of 883 frames. The third one is a picture of sunrise in the morning. The difference between the background of the scene and the moving target is very low, a total of 213 frames. The last one is a casual shot on the market. The picture has obvious shaking, a total of 778 frames. In order to better evaluate the low rank sparse matrix decomposition algorithm, the algorithm in this paper is compared with the traditional algorithm.

3. Results and discussion

3.1 Target stability of low rank sparse matrix algorithm

The stability of the low rank sparse matrix decomposition algorithm is shown in Figure 2. It can be clearly seen from the figure that under the same detection conditions, for the detection of moving objects in the same video image, five repetitive experiments were carried out. The fluctuation of the low rank sparse matrix decomposition algorithm was obviously smaller than that of the traditional algorithm. By analyzing and comparing the variance of the two sets of data, it was found that the variance of the five repeated test data of the low rank sparse matrix decomposition algorithm was 0.011, while that of the traditional algorithm was 0.024. Thus, it is intuitively seen that the stability of the low rank sparse matrix decomposition algorithm is more stable than that of the traditional algorithm and it has obvious advantages.

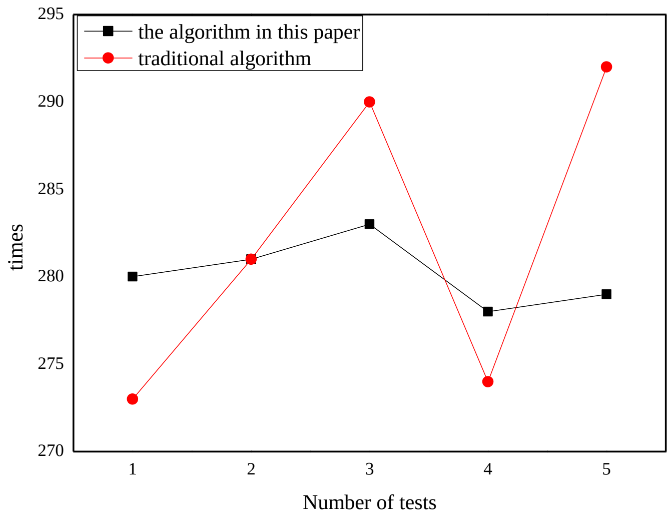

Figure. 2 Stability of low rank sparse matrix decomposition algorithm

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3.2 Operating rate of low rank sparse matrix algorithm

The operation rate based on low rank sparse matrix decomposition algorithm is shown in Figure 2. From the data in the figure, it was clearly seen that the operation rate of the low rank sparse matrix decomposition algorithm in this paper was the highest compared with optical flow method and back prime difference method. High operation rate means time saving and efficiency improvement. For the detection results of five sample objects in the figure, the speed of the algorithm in this paper was the highest. Thus, it can be said that after a number of experiments, compared with the detection rate of moving objects in video images by traditional algorithms, the algorithm in this paper has more excellent and obvious performance.

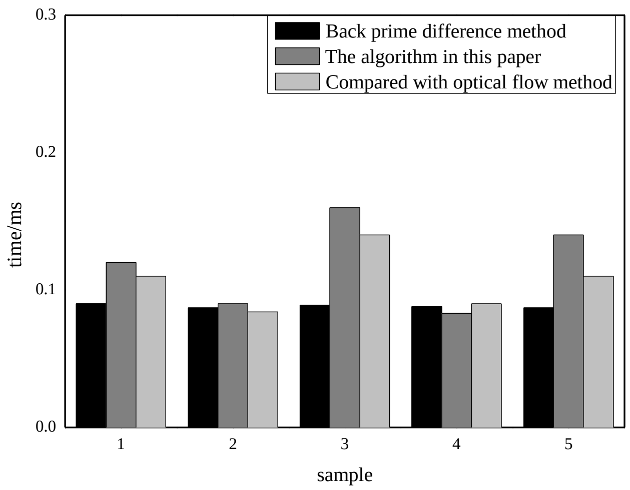

Figure. 3 Operating rate based on low rank sparse matrix decomposition

3.3 Error analysis of low rank sparse matrix decomposition algorithm

The error analysis of the low rank sparse matrix decomposition algorithm for moving target detection is shown in Figure 4. It can be seen that the error of the low rank sparse matrix decomposition algorithm in this paper was larger in the initial stage of target detection, but as the number of iterations increases, the error gradually decreased until it tended to converge smoothly. Although the error of the traditional algorithm was relatively small in the initial stage, it increased with the increase of iteration times, and did not tend to converge. The error rate was maintained at a very high level. It is found that the error rate of the low rank sparse matrix decomposition algorithm has obvious advantages over the traditional algorithm.

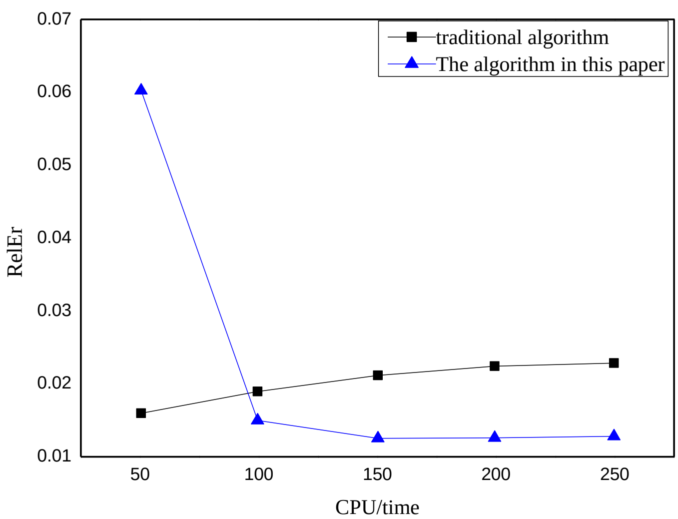

Figure. 4 Error analysis of motion target detection based on low rank sparse matrix decomposition

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3.4 Motion target detection algorithm in video images

The contrast histogram of video image moving object detection algorithm is shown in Figure 5. Compared with optical flow method, back prime difference method, and interframe difference method, the low-rank sparse matrix decomposition algorithm studied in this paper has obvious advantages in the accuracy of detection. Several other traditional algorithms have obvious errors in the detection and real situation of moving objects in image and video. The results of the algorithm in this paper are the closest to the real results. This shows that the low rank sparse matrix decomposition algorithm in this paper has higher practical value and application space in the detection of moving objects in video images.

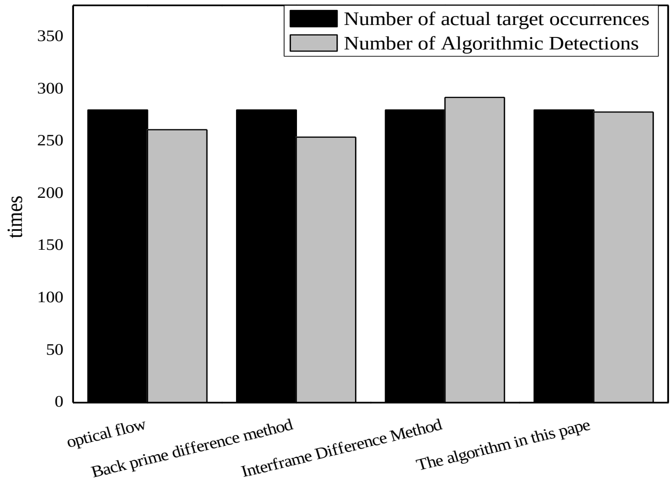

Figure. 5 The contrast histogram of video image moving object detection algorithm

4. Conclusion

The low rank sparse matrix decomposition algorithm was mainly used to precisely detect and analyze moving objects in video images, so as to study the accuracy and work condition of the algorithm. The stability, accuracy, image extraction, recovery, error, and work efficiency of the low rank sparse matrix decomposition algorithm and the tradition algorithm were compared and analyzed. The results showed that the low rank sparse matrix decomposition algorithm had obvious advantages over the traditional algorithm in terms of stability and accuracy error. The standard deviation of the data of the algorithm in this paper was 0.011, and the traditional algorithm was 0.024; the detection accuracy of the algorithm in this paper reached 93.7%, while that of the traditional algorithm was only 79.6%. The extraction and restoration were clear and without shadow, and the efficiency was improved by 37.8%. For any moving object in the video image, the detection results of the algorithm were always stable, which also showed that the efficient and normal operation of the algorithm was a comprehensive result. This paper also has some limitations. For example, the detection of moving target is a very complex work, involving very complex technology. This paper neglects the interference caused by the environment around the target in the process of algorithm detection, and the results are slightly less convincing. In addition, at present, the algorithm in this paper cannot achieve complete recovery, including color, expression and other aspects for moving target detection. Follow-up research can be more thorough and comprehensive, which will reduce the interference caused by some other factors.

Acknowledgments

Scientific Research Program Guiding Research Project of Hubei Provincial Department of Educatio n, (Project No. B2016281).

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