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Moving Target Detection and Tracking Based on Improved FCM Algorithm

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ABSTRACT

With the rapid development of computer intelligence technology, the majority of scholars have a great interest in the detection and tracking of moving targets in the field of video surveillance and have been involved in its research. Moving target detection and tracking has also been widely used in military, industrial control, and intelligent transportation. With the rapid progress of the social economy, the supervision of traffic has become more and more complicated. How to detect the vehicles on the road in real time, monitor the illegal vehicles, and control the illegal vehicles effectively has become a hot issue. In view of the complex situation of moving vehicles in various traffic videos, the authors propose an improved algorithm for effective detection and tracking of moving vehicles, namely improved FCM algorithm. It combines traditional FCM algorithm with genetic algorithm and Kalman filter algorithm to track and detect moving targets. Experiments show that this improved clustering algorithm has certain advantages over other clustering algorithms.

KEYWORDS

Genetic Algorithm, Improved FCM, Kalman Filter, Moving Target Detection and Tracking

1. INTRODUCTION

Today, vision-based moving target detection and tracking has been widely used in video surveillance, virtual reality, human-computer interaction, planet detection, behavior understanding and other fields. It has realized the functions of public safety monitoring and management, accident prevention, detection and processing, emergency deduction, monitoring of the elderly, children and disabled, and self- navigation. Visual-based moving target detection and tracking has gradually penetrated into all aspects of people's lives, and its importance has become increasingly prominent, it attracts more and more scholars and research institutions at home and abroad to participate in this field[YIN,2016].

At present, some conventional moving target detection methods include: (1) Target detection based on background modeling includes initialization of background model, model maintenance, and foreground detection and segmentation. For example, Wang et al. proposed to improve the initialization background model Median, and proposed a robust initialization model that can accommodate more than 50% of the foreground targets or noise. Its disadvantage is that it can only be used in a fixed scene environment, and it changes constantly due to changes in illumination and the changing factors of the target in the scene. Accurate and various background models need to be established, so they usually cannot meet the real-time performance request well. (2) Target detection based on foreground object modeling, the foreground object and background in training samples are respectively expressed by features, the object or background appearance model is established, and then the classifier model is obtained by classifier training. For example, the DPM target detection algorithm proposed by

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Felzenszwalb is a target shape description model trained by combining gradient histogram (HOG) features with Latent SVM. Its disadvantage is that the accuracy and robustness of the algorithm are not high under the conditions of large occlusion, small inter-class difference and large intra-class difference, large target deformation and scale change, and low image resolution [Li,2010; Wang,2019].

This paper is mainly described the target detection algorithm based on feature optical flow. The core idea of the algorithm is to calculate the optical flow of all feature points in each frame image by using feature matching of a series of adjacent images, and then perform an improved clustering algorithm on the optical flow to separate the moving target from the background, and last track the target in combination with Kalman filter. The innovation of this paper is to propose an algorithm that can automatically give the number of clusters, which is a simple and fast improved FCM algorithm, and several sets of experiments are carried out for comparative analysis. The results show that the algorithm is adaptive. And the number of moving targets is given at each moment, successfully separating the target and background.

2. FCM CLUSTERING ALGORITHM

The fuzzy C-means clustering algorithm (FCM) is simple in principle, easy to be operated and widely used. The core idea is to minimize the objective function, and to find the final class center and membership matrix. A given data set $X=\left\{x_1,x_2,\cdots,x_N\right\}$, which contains N samples, the number of clusters is C, u_{ij} is the degree of membership for the first j sample $x_j\ \left(j=1,2,\cdots,N\right)$ which belong to the Ith category $v_i\ \left(i=1,2,\cdots,C\right)$, the objective function of FCM is as follows[Gao, 2016]:

$$\begin{cases} \min & J\left(U,C\right)=\sum_{i=1}^{C}\sum_{j=1}^{N}u_{ij}^{m}\left(x_j-v_i\right)^2 \\ s.t & \sum_{i=1}^{C}u_{ij}=1 \end{cases} \tag{1}$$

Among them, M is the fuzzy coefficient, usually m is taken 2. According to the Lagrange multiplier method we obtain the clustering centers and membership degree expressions as follows [Tang, 2014]:

$$v_i=\frac{\sum_{j=1}^{N}u_{ij}^{m}x_j}{\sum_{j=1}^{N}u_{ij}^{m}} \tag{2}$$

$$u_{ij}=\frac{1}{\sum_{k=1}^{C}\left(\frac{\left(x_j-v_i\right)^{\frac{2}{m-1}}}{\left(x_j-v_k\right)^{\frac{2}{m-1}}}\right)} \tag{3}$$

The steps of the algorithm are as follows:

1. Give the data set X, the number of clusters C, fuzzy coefficient m, the maximum iterations of t_max and iterative accuracy ε ;
2. Random initialize the cluster center and membership degree;
3. Update the cluster centers and membership degrees according to the Formula (2) (3);
4. Repeat the first (3) step, until the conditions of iteration termination are satisfied.

3. IMPROVED FCM ALGORITHM

3.1. Algorithm Introduction

The improved FCM, which combines traditional FCM with genetic algorithm GA, can avoid being limited to local solutions because GA is not limited to one point in the solution space, but handles a group of points at the same time. However, because of its poor search ability and convergence speed, it is difficult to hit the extreme point, and only the approximate solution close to the global optimal solution can be found. The genetic algorithm is used to obtain the approximate solution of the global optimal solution. Then the approximate solution is used as the initial value of the FCM algorithm, and the FCM algorithm is used to segment the image to achieve adaptive image target detection.

Usually, the detection and tracking of moving objects are real-time, but the number of targets in the scene is uncertain, and it is likely to change all the time. This requires the clustering of the optical flow with fast, adaptive capacity. It can automatically determine the number of targets for each moment. This section will be based on the classic FCM algorithm, and improve it, so that it has a fast convergence and can automatically determine the number of clusters [Li, 2012].

3.1.1. The Determination of the Number of Cluster C

As mentioned in the first section, the main idea of automatically determining the number of clusters is to use some specific criteria functions to determine the optimal number of clusters. In general, the purpose of the criterion function is to ensure that the internal spacing of classes is very small, space between class and class is large. Here we use the DBI function to determine the number of clustering, DBI clustering algorithm is a kind of measurement, and the specific understanding is as follows.

Give the cluster center v_i and v_j, both are the P dimensional vector, the distance between classes is defined as follows:

$$d\left(v_i, v_j\right) = \sqrt{\sum_{h=1}^{p}\left(v_{ih} - v_{jh}\right)^2} \tag{4}$$

Inner-distance of class is defined as follows:

$$S_i = \frac{1}{\left|v_i\right|}\sum_{x \in C_i}\sqrt{\sum_{h=1}^{p}\left(v_{ih} - x_h\right)^2} \tag{5}$$

x is the data sample of the I class, v_i is the class center, $\left|v_i\right|$ is the number of data samples in class I, S_i is the standard deviation between the data sample and the class center of the class I.

DBI indicators are defined as follows:

$$DBI = \frac{1}{C}\sum_{l=1}^{C} \max\left\{\frac{S_i + S_j}{d\left(v_i, v_j\right)}\right\} \tag{6}$$

Note: We will get different DBI value for the different clustering number C, the smaller the DBI value is, the better the obtained clustering effect of the corresponding partition is.

3.1.2. Genetic Algorithm

Genetic algorithm is also known as evolutionary algorithm. The core idea refers to the biological theory of evolution, the problem to be resolved is simulated into a biological evolution process, and is produced the next generation of solutions through reproduction, crossover and mutation operations, and the solution of the low fitness function value is removed in turn, keep the solution which has high value of fitness function. According to these rules, after continuous evolution of N generations it will have great chance to have evolved individuals with higher values of adaptive function. Algorithm flow chart is shown in Figure 1 [Zhang, 2017].

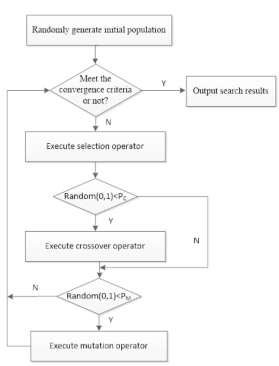
The main steps of genetic algorithm are as follows:

1. **Initialization:** Set the algebraic counter t=0, and T as the maximum evolution generations, randomly generated M individuals as the initial population P (t);
2. **Individual evaluation:** Calculate the fitness value of each individual in P (t);
3. **Selection operation:** The selection operator is used to the group;
4. **Crossover operations:** The crossover operator is applied on the group;
5. **Mutation operation:** The mutation operator is acted on the group, and get the next generation of P(t+1) through the above operations;
6. **Determine the termination conditions:** If meet the maximum number of iterations, then terminate and output the solution, otherwise turn to the step 2.

3.1.3. The Improved FCM Algorithm

Considering that the classical FCM algorithm is sensitive to the initial position, it also needs to be given the number of clusters in advance, which is not adaptive. In this paper, GA and FCM are combined. The GA algorithm is first used to obtain the initial class centers, and then the FCM algorithm is

Figure 1. Flow chart of GA algorithm



executed to obtain the clustering result. In addition, the DBI criterion function is used here to optimize the number of clusters and finally appropriate number of clusters are given.

The execution flow of the GA-FCM algorithm is as follows:

1. Initialize some parameters, including the number of clusters C, the fuzzy parameter q ($1 \leq q \leq \infty$), the average value t' of the data, and the iteration termination parameter β;
2. Initialize C cluster centers vi0 (i=1, 2, ..., C) using the GA algorithm;
3. Calculate uij, the function expression is:

$$u_{ij} = \frac{1}{\sum_{i}^{c}\left[\frac{\| t_j - v_i \|^2 + \theta \| t'_j - v_i \|^2}{\| t_j - v_l \|^2 + \theta \| t'_j - v_l \|^2}\right]^{\frac{1}{q-1}}} \tag{7}$$

4. Calculate the new cluster centers, that is vi1, and the corresponding function is expressed as:

$$v_i^{\,e} = \frac{\sum_{j=1}^{n} (u_{ij}^{\,e})^q t_j + \theta \sum_{j}^{n} t'_j}{\sum_{j=1}^{n} (u_{ij}^{\,e})^q} \tag{8}$$

In Formula (8), i has a value range of [1, C], and a neighborhood factor is added to the function. The added variable set is {θt'1, θt'2, θt'3.......θt'n}, the updated cluster center point is represented as vi1.

5. If the difference between the old and new clustering centers is less than β, then all the clustering centers are output, otherwise is returned to step 3 and further explore the correlation between data objects;
6. Output the final cluster centers (a, b).

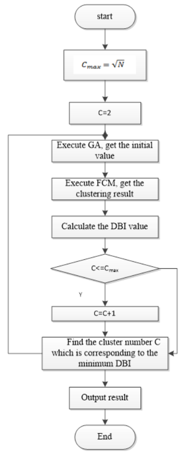
The flow chart of the improved FCM algorithm proposed in this paper is shown in Figure 2.

As above, the range of the number of cluster C is still given to $2, \ldots, \sqrt{N}$, and the maximum number of clusters C is $\sqrt{N}$. The initial value of the cluster number C is taken 2, first run GA algorithm on the total sample, and get the optimal clustering number C and clustering center. Then the optimal number of cluster number C is as the initial clustering number of FCM algorithm for clustering, and then the cluster result is obtained. Calculate the DBI value according to the results of this clustering at this time. And the like, calculate $\sqrt{N} - 1$ times DBI value. Compare these DBI values, and find the number of cluster C corresponding the minimum DBI value and that C is the final optimal number of clusters.

The main steps of the algorithm are as follows:

1. Give a set of samples $X = \left\{x_1, x_2, \cdots, x_N\right\}$, and the maximum upper bound for the number of clustering C is given as $C \leq \sqrt{N}$;

Figure 2. The flow chart of improved FCM



2. For each cluster number $C = 2, \cdots, \sqrt{N}$, run $\sqrt{N}$ times FCM algorithm, and get $\sqrt{N}$ clustering results, that is, for the $\sqrt{N}$ cluster number C, get the initial cluster center after the running of the GA algorithm, use the FCM algorithm to cluster, get $\sqrt{N}$ clustering results;
3. The Formula (3) is used to calculate the value of the criterion function according to the $\sqrt{N}$ cluster results and compare the value of each function;
4. Find the clustering number C corresponding to the minimum DBI value and that C is the optimal value;
5. Output the final result.

4. FEATURE OPTICAL FLOW BASED ON IMPROVED FCM ALGORITHM AND KALMAN FILTER FOR MOVING TARGET TRACKING

4.1. Algorithm Introduction

In this paper, an improved FCM algorithm above and an improved optical flow method are proposed to detect moving targets. After clustering the moving targets, the coordinates and velocity values of the moving targets are obtained. Furthermore, a Kalman filter based on block matching is used to track the moving targets.

The coordinates and the speed of the feature points of the moving objects can be easily obtained through the feature optical flow algorithm at any time. In the process of practical tracking, as the distance between the front and back frames is very short, distance traveled of the moving target is very short, so it can be considered that the moving object is moving at a constant speed in the fixed time interval. Give Kalman filter system state x_k as a vector $\left(x, y, u, v\right)^T$, in which x and y represents the position of optical flow of the target in the axis X, Y, and u and v are the speed of optical flow targets in the axis X, Y. According to the given conditions, the expression of state transition matrix is obtained [Meng,2013; CHEN, 2018]:

$$A_{k,k-1} = \begin{bmatrix} 1 & 0 & \Delta t & 0 \\ 0 & 1 & 0 & \Delta t \\ 0 & 0 & 1 & 0 \\ 0 & 0 & 0 & 1 \end{bmatrix} \tag{9}$$

Among them Δt is the interval from t_{k-1} to t_k.

According to the relationship between the system state and the observed state, the observation matrix can be introduced as follows:

$$H_k = \begin{bmatrix} 1 & 0 & 0 & 0 \\ 0 & 1 & 0 & 0 \end{bmatrix} \tag{10}$$

The covariance matrix of w_k and v_k is respectively defined as follows:

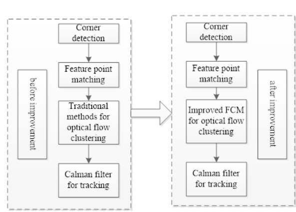
$$Q_k = \begin{bmatrix} 1 & 0 & 0 & 0 \\ 0 & 1 & 0 & 0 \\ 0 & 0 & 1 & 0 \\ 0 & 0 & 0 & 1 \end{bmatrix} \tag{11}$$

$$R_k = \begin{bmatrix} 1 & 0 \\ 0 & 1 \end{bmatrix} \tag{12}$$

In this paper, the improved FCM algorithm in Section 2 is applied to feature optical flow method for target detection. After gathering moving targets, the coordinates and velocity of moving targets are obtained, and then Kalman filter tracking is carried out. Comparision between the traditional feature optical flow and Kalman filter moving target tracking and the improved algorithm is as follows in the flow chart in Figure 3 [Huang, 2015; Bouwmans T., 2014].

As Figure 3 shows, the method mentioned in section 1 are used for optical flow cluster before improvement and we use the improved FCM algorithm for the optical flow cluster after improvement.

Figure 3. Flow chart of Comparison process



5. EXPERIMENT AND RESULT ANALYSIS

5.1. Experiment

The computer hardware environment for the experiment is the quad core clocked at 2.6GHz CPU, 4G memory, and the programming environment is VC++6.0 and OpenCV3.0 image development kit. The experimental object is the traffic video, the image resolution of the video sequence is 320 * 240, and frame rate is 25 frames per second, optical flow number is 200. How to detect the vehicles of different sizes and shapes and track them, which is one subject of the experiment. This system can effectively detect moving vehicles in video, and mark the detected vehicle using rectangle, a rectangular box marks a car. The initial interface of the system is shown in Figure 4.

Click “import video”, the results window is shown in Figure 5.

It can be seen from the results of the display system, optical flow method at the moment in the current frame detected 200 points of optical flow, the improved FCM algorithm marked these optical flow points into 3 clusters, three rectangular boxes were used to mark them.

5.2. Results Analysis

Here we still choose three representative traffic video as the experimental object, and analyze the clustering of the vehicles. The types of the three segment video are: 1) the background is single and there are many vehicles; 2) the background is unitary, and there are not many vehicles; 3) the background is complex, there are not many moving vehicle. The sizes of the three videos of vehicles are all 10M, pixels are 320*240, video sample is 24 bits, frame rate is 25 frames/sec. Screenshot in each video is shown in Figure 6 and Table 1.

In each segment of the video, the clustering accuracy of each algorithm for the moving objects is calculated as follows:

Figure 4. Initial interface of system

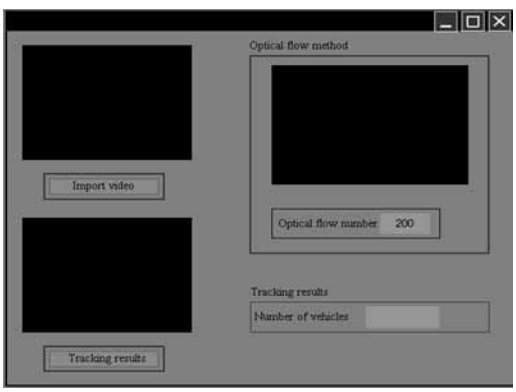


Figure 5. The experimental results

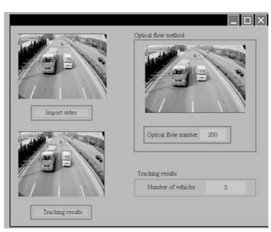


Figure 6. Screenshot of the video scene

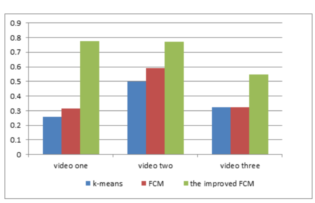
Table 1. Clustering results of moving vehicles

Video	Total Number of Actual Vehicles in Video	k-Means	FCM	The Improved FCM
Video one	89	23	28	69
Video two	22	11	13	17
Video three	31	10	10	17

Table 2. Clustering accuracy table for moving vehicles

Video	Total Number of Actual Vehicles in Video	Experimental Results	Clustering Accuracy
Video one	89	69	77.5%
Video two	22	17	77.3%
Video three	31	17	54.8%

Figure 7. Comparison of clustering accuracy of each algorithm



$$clustering\ accuracy = \frac{the\ vehicles\ clustered}{the\ actual\ \ total\ number\ of\ the\ vehicles} \tag{13}$$

According to Formula (13), the values of the improved clustering accuracy in each video can be calculated as shown in Table 2.

The clustering accuracy of each algorithm for the three segments of videos is compared as shown in Figure 7.

The above experimental results can be observed:

1. In this paper, the improved FCM algorithm has better clustering effect, and the performance of the cluster accuracy is better than that of the K-means. This is due to that the improved FCM algorithm sacrifices a certain amount of time to gain a higher clustering precision;
2. In the experiment, we can see that it is worth the increase of a small amount of running time in exchange for the increase of the clustering accuracy. As within a certain period of time the detection and tracking of the moving target as accurate as possible is the most important. In summary, the target tracking will use the improved FCM algorithm to cluster the optical flow.

The advantage of the improved FCM is that the clustering accuracy is better than other adaptive algorithms, and it can cluster the number of targets well. The disadvantage is that it consumes more time, which is not beneficial to solve the real-time traffic problems. The improved FCM algorithm is better for the complex scene, and it has better effect for the target detection and tracking in messy background in real time traffic scene, and can get the moving vehicles intelligently and accurately from the complex background, and do the effective positioning and tracking. Table 3 shows the clustering results of moving vehicles before and after improvement.

From the experimental results, it can be observed that feature optical flow based on the improved FCM algorithm and Kalman filter motion target tracking method proposed in this paper can achieve better detection and tracking of moving vehicles in traffic video. Specific analysis is as follows:

1. In video one, the correct rate before and after improvement both are high for detection and tracking of the vehicle. This is because the experimental scene is single, and the interference of the algorithm is relatively little. And also because the improved FCM algorithm for optical flow clustering has much more advantages compared with the traditional method of optical flow clustering, so its correct rate is higher than the traditional algorithm. The scene has much traffic, detection and tracking are prone to have the following problems: 1) the two vehicles or more cars are too close in driving process, it seems to be clustered as one class; 2) sometimes the large vehicles will be clustered for multi class; 3) when the vehicles overlap, maybe are clustered as a class;

Table 3. Clustering results of moving vehicles before and after improvement

Video	The Actual Number of the Vehicles in the Video	The Result of the Experiment		Correct Rate	
		Before Improvement	After Improvement	Before Improvement	After Improvement
Video one	22	15	17	68.2%	77.3%
Video two	89	66	69	74.2%	77.5%
Video three	31	16	17	51.6%	54.8%

2. The correct rate of video one and video two are close, the reason is that the background of the video one and video two is relatively simple, and have less interference information. And the correct rate of video two is a bit lower than the video one, which is because the background of the video two is slightly more complex, there are more instructions in the video two, and the interference is increased. Such as the road indication information are error detected as feature points, but the vast majority of similar interference in the optical flow clustering will be shielded, and its influence is not very big, thus the correct rate of the vehicles detection and tracking in video one and video two are close;
3. The correct rate of the video three is relatively low, it is mainly because that the video scene is much more complex, the interference information on both sides of the vehicle lane is much, such as trees affected by the wind, parked vehicles, pedestrians, etc. This fully shows that interference has much influence on the experimental results, how to improve the anti noise and stability of the algorithm is the problem we need to consider;
4. In the three videos, the correct rate of the improved algorithm for vehicle detection and tracking in traffic video is greater than before, and it shows that the improved FCM algorithm in this paper has played a very good effect in optical flow clustering, and the improved feature optical flow and Kalman filter motion target tracking algorithm can be more effective for the detection and tracking of the moving vehicles.

6. CONCLUSION

Firstly, the improved FCM algorithm is designed by combining the characteristics of FCM algorithm and GA algorithm. Secondly, the improved FCM feature optical flow algorithm and Kalman filter algorithm are elaborated. Finally, the two algorithms are combined to analyze the running vehicles in traffic video. Experiments show that the combined two algorithms can effectively detect and track moving vehicles. Especially in the case of complex scenes, occlusion, different vehicle types and sizes, it can accurately track and detect the target. The algorithm has good effect and strong robustness, and has high accuracy in detecting the target. However, the algorithm does not have an advantage in speed, and further improvements are needed in improving the speed of the algorithm in the future.

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