Crowd Behaviors Analysis and Abnormal Detection based on Surveillance Data

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Abstract—Crowd analysis and abnormal trajectories detection are the hot topics in computer vision and pattern recognition. As more and more video monitoring equipments are installed in public places for public safety and public management, researches become urgent to learn the crowd behavior patterns through the trajectories obtained by the intelligent video surveillance technology. In this paper, the FCM (Fuzzy c-means) algorithm is adopted to cluster the source points and sink points of trajectories that are deemed as critical points into several groups. Naturally, the trajectory clusters can be acquired. After refining them, the feature information statistical histogram for each one which contains the motion information will be built after refining the trajectory clusters with Hausdorff distances. Eventually, the local motion coherence between test trajectories and refined trajectory clusters will be used to judge whether they are abnormal.

Keywords: Crowd analysis, abnormal trajectories detection, FCM, feature information statistical histogram

I. INTRODUCTION

As more and more video monitoring equipments are installed in public places for public safety and public management, researchers can learn the motion patterns of crowds and do further studies by analyzing the observed data. As the traditional methods can not be applied in the analysis of unstructured situations, to overcome this problem, we propose a new approach. The approach adopted in our research focuses on the motion patterns learning and abnormal trajectories detecting. Our approach has several advantages: Firstly, FCM[8] is used to cluster the source and sink points, and the hidden unstructure information of the unstructured scene will be learned. Secondly, according to the hidden unstructure information, we will get the training trajectory clusters. And the parallel coordinates which can represent data in high-dimension are used to describe the motion patterns of crowd. Thirdly, we can judge which trajectory cluster the test trajectory most possibly belongs to with the hidden unstructured information and our training trajectory clusters learned before. Then we just need to make a compared between the test trajectory and the cluster which it most possibly belongs to, instead of the whole clusters. As a result, the computational efficiency is improved greatly.

II. RELATED WORK

The data observed by monitoring equipments in a scene usually can not be studied directly. Researchers, like Sugimura et. al. [2], proposed a method for tracking persons in the crowd. After transforming the observed data into trajectories of tracking objects, the crowd behaviors can be analyzed. Crowd behavior analysis has three major aspects: motion patterns learning, abnormal behaviors detection and behaviors prediction. Next, we will briefly describe some of the achievements on them.

Generally speaking, motion patterns learning is the primary step in the related studies. It practices the regular motion trajectories, namely, motion patterns, by using the observed data. For instance, Fatih Porikli et.al[3] learned the trajectory patterns by computing affinity matrices and applying eigenvector decomposition. Few years later, an improved DBSCAN (Density-Based Spatial Clustering of Applications with Noise) method was used to divide the motion flows into different patterns[4].

Abnormal behaviors detection aims at identifying the movement behaviors which are obviously different from other motion tracks or have low probabilities of occurrence by using the motion patterns discovered before. Claudio Rosito Jung et.al. [1] proposed a approach that used 4-D histogrm to make abnormal detection. Stauffer et.al. [5] modeled each pixel as a mixture of Gaussians, used an on-line approximation to update the model at the same time.

Behaviors prediction is a subject which attracts much attention. Researchers desire to forecast the next moving region or semantic behavior based on the priori knowledge and motion patterns of moving objects. Josh Jia-Ching Ying et.al[6] combined the geographic features and the semantic features of users’ trajectories together, and then it evaluated the next location of a mobile user based on the frequent behaviors of similar users in the same cluster.

In addition, other aspects of crowds also appeal to scholars. Jan Sochman et.al [7] proposed an automatic on-line inference of social groups based on the Social Force Model in crowded scenarios.
make all the trajectories described by the flow vector set with the same number. Eventually, the resample points computed by our algorithm can help to access the similarities between trajectories in the next processes easily.

B. Critical Points Clustering

In order to analyze the behaviors of crowd, we’d better to cluster the similar trajectories into one same group for further research. In our research, we extract the critical points of all tracks: source point and sink point of each trajectory, which usually appear at the edge regions of the scene. As so far, researchers have developed a lot of clustering methods, it is pointed out that the standard FCM algorithm is robust to the scaling transformation of the dataset, while others are sensitive to such transformation.

In our research, the FCM algorithm is performed for critical points clustering. And then we can obtain N points groups. Obviously, we can get $N \times N$ motion patterns of crowd trajectories roughly.

C. Build Feature Information Statistical Histograms for Refined Clusters

After the previous works, we have gotten the rough similar trajectories. A group of similar trajectories means a pattern of crowd behaviors. In order to learn the behavior rules better, we should find the center trajectory whose sum of the Hausdorff distances to other trajectories in its cluster is minimum. And then those trajectories that have unreasonable Hausdorff distances to the center trajectory of its cluster should be removed. As a result we achieve refined trajectories clusters and then build the feature information statistical histograms for them.

After the previous works, we have gotten the rough similar trajectories. In order to learn the behavior rules better, we should remove the trajectories that have unreasonable Hausdorff distances to the center trajectory of its cluster to refine trajectory clusters, and transform sample $(x, y, \theta, v)$ to build the feature information statistical histograms which can describe the probability distributions of trajectories in the scene.

In order to get the histograms. First of all, we should discretize each trajectory as a sequence of $(x_i^d(t), y_i^d(t), \theta_i(t), v_i(t))$. The feature information statistical histogram $H_k$ related to the $k$th cluster is built by spreading the according to a kernel $g$

$$H_k(x^d, y^d, \theta^d, v^d) = \sum_{i=1}^{N_k} \sum_{t=1}^{N_f(i)} g(x^d - x_i^d(t), y^d - y_i^d(t), \theta^d - \theta_i(t), v^d - v_i(t))$$

Where $N_k$ is the number of the trajectories in kth cluster and $N_f(i)$ is the length of the ith trajectory in cluster k and $g(x, y, \theta, v)$ is the spreading kernel.

$$g(x, y, \theta, v) = g_1(x, y)g_2(\theta)g_3(v)$$
In order to build the feature information statistical histogram for each cluster, three steps should be followed:

1) The first step is to discretize the information of each point in $i$th trajectory, we change the location of the moving object $(x, y)$ to a discrete value $(x^d, y^d)$, where $x^d \in \{0, 1, ..., N_x-1\}, y^d \in \{0, 1, ..., N_y-1\}$ and $N_x$ is the number of lines of the image, $N_y$ is the number of columns of the image.

2) Then we transform the local direction vector $\theta$ into a discrete value $\theta_d$, which has $N_\theta$ levels, and each level comprises a circular sector with internal angle:

$$\theta_d \in \{\theta_0, \theta_1, ..., \theta_{N-1}\}, \theta_j = \frac{j}{N_\theta} 2\pi$$

At the same time, the velocity $v$ is turned into a discrete value $v^d$ within $N_v$ levels (low, middle and high)

$$v^d = \begin{cases} 
0&(\text{low speed}) \quad \text{if } 0 \leq v < v_t \\
1&(\text{medium speed}) \quad \text{if } v_t \leq v < v_h \\
2&(\text{high speed}) \quad \text{if } v_h \leq v 
\end{cases}$$

$$v_t = \mu_v - k\sigma_v, v_h = v_t = \mu_v + k\sigma_v$$

where $k$ control the velocity, set $k=2$. In each cluster, we will obtain an array about the velocity of trajectories, $\mu_v$ is the mean of the array, and $\sigma_v$ is its variance.

3) The third step is to compute the histograms with Equation (3) and Equation (4). For $g(x, y)$ in Equation (4), a discrete Gaussian function is the best choice. And $\sigma$ is the standard deviation of function. The normal spatial distribution in n-dimensional space is shown as in Formula (8).

$$g(r) = \frac{1}{\sqrt{2\pi}\sigma^2}e^{-\frac{r^2}{2\sigma^2}}$$

As the research works on a 4-dimensional space, we can transform the above equation into Formula (9).

$$g_1(x, y) = \frac{1}{2\pi\sigma^2}e^{-\frac{x^2 + y^2}{2\sigma^2}}$$

Then we compute the $g_2(\theta)$, the second part of Equation (4), as in the following equation,

$$g_2(\theta) = \max\{0, 1 - \frac{|\theta|_{\text{ang}}}{\Delta \theta_{N\theta}}\}$$

Where $\theta \in \{\theta_0, ..., \theta_{N\theta-1}\}, \theta_j$ is a discrete direction value, $\Delta \theta_{N\theta} = 2\pi/N\theta$ and $|\theta|_{\text{ang}} = \min\{\theta, 2\pi - |\theta|\}$.

The last item of the spreading kernel is $g_3(v) = \delta(v)$(11) , $\delta(v)$ is the discrete Dirac Delta(unit impulse) function. Eventually, we can get a histogram with dimensions $N_x \times N_y \times N_\theta \times N_v$ for each cluster. It should be noticed that a feature information statistical histogram is computed for each cluster and it represents a motion pattern.

V. ABNORMAL TRAJECTORY DETECTION

According to the result of previous experiments, the refined clusters and their histograms have been obtained to help us judge whether the test trajectories are abnormal or not. We will use the following formula to calculate the local consistency between the given trajectory and the $k$th cluster histogram $H_k$.

$$d_k(t) = H_k(x^d(t), y^d(t), \theta^d(t), v^d(t))$$

If they are local consistent at time $t$, the value of $d_k(t)$ will be large. Otherwise the value will be small. These abnormal trajectories are that most sample points of them have low level values of $d_k(t)$.

We should choose a threshold value $T_k$ for each cluster. If $d_k < T_k$, we will regard the trajectory as local abnormal at time $t$. Each trajectory of $k$th cluster should be calculated the value of $d^*_k(t)$, then we can obtain a set $D_k$ of $k$th cluster as in Equation (14).

$$D_k = \bigcup_{i=1}^{N_x} \bigcup_{t=1}^{N_y} \{d^*_k(t)\}$$

where $T_k$ is r-quantile of the distribution of $D_k$.

VI. EXPERIMENT RESULTS

This section will demonstrate the results of experiment based on the previous work. All the experiment data are from the pedestrian trajectory database of Edinburgh University. In our research, we draw 20000 pedestrian trajectories randomly to analyze and study the motion patterns of them.

A. Critical Points Clustering

Firstly, we extract the source and sink points of all the trajectories in our database. According to Figure 2(a)-(b), we can see that the entry regions and exit regions are almost bidirectional; so we merge source set and sink set to a whole point set for further learning. After that, we should group all the points into several clusters by FCM. In this study, the number of clusters that can lead the best result will be 12. All point clusters are shown in Figure 2(c). Through grouping the critical point set into several clusters some structure information of the giving scene can be learnt at this stage.
B. Trajectory Motion Patterns

In the first step, 12 point clusters can be found. Then, we regard the trajectories which appeared at region A and disappeared at region B as a rough trajectory cluster. That is to say, we have achieved 144 rough trajectory clusters. Several prominent trajectory clusters are shown in Figure 3.

Secondly, with the purpose of learning crowd motion regularity easily and accurately, we need to refine the trajectory clusters obtained before. A group of similar trajectories means a pattern of crowd behaviors. In order to learn the behavior rules better, we should find the center trajectory whose sum of the Hausdorff distances to other trajectories in its cluster is minimum. And then those trajectories that have unreasonable Hausdorff distances to the center trajectory of its cluster should be removed. As a result we achieve refined trajectories clusters and then build the feature information statistical histograms for them.

Moreover, building feature information statistical histograms for refined clusters can helps us learn the probability distribution of trajectories. In order to describe all the feature information about the clusters, we adopt the parallel coordinates as shown in Figure 4.

Parallel coordinates is a common method for the high dimension data visualization. A high dimension data point \((x^d, y^d, \theta^d, v^d)\), \(H_k(x^d, y^d, \theta^d, v^d)\) can be expressed as a broken line. The inflection points of it are located at each parallel axis and they can show the value of corresponding dimension. What’s more, the value of \(H_k(x^d, y^d, \theta^d, v^d)\) shows that the sum of the probabilities of each location sample point in cluster \(k\) belongs to the statistic class \((x^d, y^d, \theta^d, v^d)\).

C. Abnormal Detection

Eventually, we extract 5000 new trajectories to make abnormal detections. The critical points of these test trajectories are divided into 12 groups according to the regions they belonged to as shown in Figure 5.

Moreover the status of test trajectories is displayed in TABLE I. Each element in TABLE I represents the number of test trajectories that most possible belong to each training cluster learned before. Then the later work can determine the correctness of our preliminary judgments.

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Next, we detect the local motion coherence between test trajectories and histogram set of refined trajectory clusters, the value of \(r\) mentioned in section V is set to 20. In Figure 6, figure (a) shows most of trajectory 42305(the index of this trajectory in test set is 42305) are local coherence with the histogram of cluster2-12. Then in (b), most of the test trajectory 39206 the index of it is 39206 are not local coherence with the same histogram. So we regard trajectory 39206 as an abnormal one.

The trajectory, most parts of which are coherence with the histogram will be regarded as normal. Otherwise it will be reckoned as an abnormal trajectory. Several prominent detection results are shown in Figure 7. The refined trajectory
clusters on the left, the normal trajectories for them on the middle and the abnormal trajectories on the right.

In order to describe the effect of our abnormal detection step better, we also prepare another test set with 10000 trajectories. The status of it is displayed in Table II. And several detection results are show in Figure 8. It proves the effect of our approach again.

### Table II: Entry-exit Region Transferring Matrix of Test Set2

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We can see that if the pass regions of a test trajectory are different from most members in its corresponding cluster, it will be found out as an abnormal one, just as most in Figure 7 and 8. Even though some trajectories seem similar with other members in corresponding cluster in spatial aspect, the motion direction or moving velocity may have distinct differences. They are also deemed to have another motion tendency and also be regarded as abnormal, like the examples in the third line of Figure 7.

### VII. Conclusion

In this paper, we have done some progressive work in the crowd behaviors analysis and abnormal trajectory detection. Experiment result indicated that the output (normal trajectories) produced accurately by our method was mostly coherent with the test cluster. The advantage of our approach is that the hidden unstructured information of the unstructured scene are learned on the training step, so we can judge which trajectory cluster the test trajectory most possibly belongs to with it. Then on the detecting step, the test trajectory just needs to compare with the trajectory cluster which has a high motion consistency with it, instead of the whole clusters. As a result, the computational efficiency is improved greatly.

In the future, the following work can be carried out as improvements of the method: the more optimal cluster algorithm for critical points clustering should be implemented for learning the cluster number automatically, and the behavior prediction can use the motion patterns obtained in section IV to predict the next moving region and semantic behavior.

### REFERENCES


