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Crowd behaviors analysis and abnormal detection based on surveillance data *, * *

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ABSTRACT

Crowd analysis and abnormal trajectories detection are hot topics in computer vision and pattern recognition. As more and more video monitoring equipments are installed in public places for public security and 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, and then the trajectory clusters can be acquired. The feature information statistical histogram for each trajectory cluster which contains the motion information will be built after refining them with Hausdorff distances. Eventually, the local motion coherence between test trajectories and refined trajectory clusters will be used to judge whether they are abnormal.

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1. Introduction

As more and more video monitoring equipments are installed in public places for public security and management, researchers can learn the motion patterns of crowds and do further studies by analyzing the observed data. Most traditional methods are applied only in structured situations. To overcome this problem, a new approach is proposed for the analysis in unstructured scenes, which focuses on the motion patterns learning and abnormal trajectories detection. First, FCM [1] is used to cluster the

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source and sink points of trajectories, and the hidden structure information of the unstructured scene will be learned. According to the hidden structure information, we will get the training trajectory clusters. For each trajectory cluster, the statistical feature information will then be built to describe the motion patterns of the crowd, and the parallel coordinates which can represent data in highdimension is implemented to visualize the statistical feature information of motion patterns. At the time of testing, the test trajectory is first judged on the hidden structured information to find which motion pattern of trajectory cluster that the test trajectory most possibly belongs to. Then, for detecting anomaly, instead of comparing every cluster, it only makes a comparison between the test trajectory and the statistical feature information of the motion pattern that the test trajectory most possibly belongs to. Hence the computational efficiency improved greatly.

Fig. 1 shows the framework of our approach, which roughly includes five stages: (1) preprocessing: resample to normalize trajectory length; (2) FCM clustering: cluster

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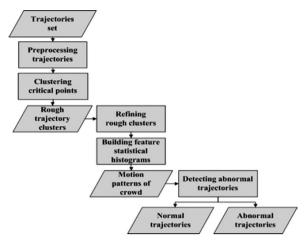


Fig. 1. Framework of crowd analysis and abnormal detection.

critical points and get rough trajectory clusters; (3) refining rough clusters with Hausdorff distance; (4) building motion patterns for each cluster by feature information statistical histogram; (5) detecting abnormal trajectories through coherence test.

2. Related works

The data observed by monitoring equipments in a scene usually cannot 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. In the following paper, we will briefly describe some of the achievements made in this area.

Generally speaking, motion patterns learning aims to build the regular motion trajectories, i.e., 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. [5] proposed an approach that used 4-D histogram to make abnormal detection. Stauffer et al. [6] modeled each pixel as a mixture of Gaussians, and used an on-line approximation to update the model at the same time.

Behaviors prediction tends to forecast the next moving region or semantic behavior based on the prior knowledge and motion patterns of moving objects. Josh Jia-Ching Ying et al. [7] combined the geographic features and the semantic features of users' trajectories together, and then 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 Šochman et al. [8] proposed an automatic on-line inference of social groups based on the Social Force Model in crowded scenarios.

3. Crowd motion patterns learning

3.1. Trajectory preprocessing

In most researches, the trajectory will be represented by a sequence of flow vectors.

$$F_n = \{f_1, f_2, \dots, f_n\} \tag{1}$$

where n is the length of the trajectory, the flow vector in Eq. (1) is formed by a tetrad as follows:

$$f_n = \langle x(t_n), y(t_n), \theta(t_n), v(t_n) \rangle \tag{2}$$

It contains the spatial, direction and velocity information of the trajectory at time t_n .

As people pass the scene from different regions and the speed of them is not uniform, the researchers always make some preprocessing to match their needs. That is to say, we should let each trajectory be represented by the same number of flow vectors. The resample based on one dimension linear interpolation is used in our approach to realize the normalization. Eventually, the resample points can help to access the similarities between trajectories in the next process easily.

3.2. Critical points clustering

In order to analyze the behaviors of the crowd, we would better cluster the similar trajectories into one same group for further research. In our research, the critical points (source points and sink points) of all trajectories which usually appear at the edge regions of the scene should be extracted. Researches have pointed out that the standard FCM algorithm is robust to the scaling transformation of the dataset, so it is performed for critical points clustering.

FCM is a clustering algorithm based on division. It divides all the data vectors into c fuzzy sets, and estimates the center of each clustering group. The cost function (or objective function) of FCM is

$$J(U, c_1, ..., c_c) = \sum_{i=1}^{c} J_i = \sum_{i=1}^{c} \sum_{j=1}^{n} u_{ij}^m d_{ij}^2$$
 (3)

where u_{ij} is the membership degree between sample j and group i, ci is the center of group i, $d_{ij} = \|c_i - x_j\|$ is the Euclidean distance between the center of group i and the data point j, which is also a weighted index number. The algorithm strives to make the cost function of the dissimilarity index to a minimum degree. It is a simple iterative process. And then we can obtain N points groups.

3.3. Feature information statistical histograms building for refined clusters

After the previous work, the rough similar trajectory clusters can be obtained. A group of similar trajectories may mean a pattern of crowd behaviors. In order to learn

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