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ANOMALY DETECTION IN CROWDS BY FUSION OF NOVEL FEATURE DESCRIPTORS

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ABSTRACT

Anomaly detection in high-density crowds is considered as an important research problem. Detecting anomalous crowd behavior is a complex problem due to unpredictable human behaviors and complex interactions of individuals in groups. In this paper, we present a supervised approach to detect anomalous trajectories. The proposed method has four subsequent steps. In the first step, we extract trajectories from the input video sequence. In the second step, we compute novel features from these trajectories. In the third step, we classify each trajectory into two classes, i.e., anomalous and normal. In the fourth step, we employ a clustering algorithm to cluster all anomalous trajectories. The resultant cluster indicates the anomalous regions in the scene. We evaluated the proposed approach on two publicly available benchmark datasets. From experimental results, we demonstrate the proposed method outperforms other state-of-the-art methods.

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1 INTRODUCTION

Crowd monitoring is important for public safety and security. With the rapid population growth, public events, like concerts, religious and political gatherings, and marathons face crowd disasters events. These events serve peaceful purposes. During recent years, high-density crowd analysis achieves much attention from the research community. For crowd monitoring, crowd managers and municipality install multiple cameras in different locations to cover a wider picture of the event. The current practice of crowd monitoring is based on manual analysis, where an analyst monitors these events through a TV screen. Such manual analysis of the crowd is a hectic job and usually results in errors due to a lack of human capabilities. Therefore, there is a need for an automatic analysis of the crowd. During recent years, a significant amount of work is reported in the literature to automate the crowd analysis task through computer vision [15]. However, researchers are still facing different

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challenges in automatically understanding the crowd.

One of the major tasks in video surveillance is to precisely detect and localize anomalous events. An anomaly in the crowd refers to any undesirable event that may pose threat to public safety and security. Generally, anomalous events occur very rarely compare to normal events. To reduce the human efforts and to respond timely to anomalous events, automatic detection of anomalous is the urgent need of current time. The main goal of anomaly detection is to timely respond to the events that tend to deviate from normal behavior. Therefore, the task of anomaly detection is to filter anomalous scenes from normal ones. We can classify anomalies into different classes once we precisely detect them.

Several strides have been made during recent years to develop methods and approaches to detect an anomalous event, for example, violence and panic detector [19] and car accident detector [10], [25]. However, these methods have limited practical application since these methods cannot be generalized to other common anomalous events.

It is complicated to define anomaly since anomalous events are complicated and diverse in nature and it is hard to list all anomalous behaviors. For a good anomalous model, it is desirable that the model requires minimum data and should not rely on previous information about the anomalous event. The best representative anomalous methods are sparse-coding approaches [16], [30] that achieved state-of-the-art performance. These models consider videos that mainly contain anomalous content. However, in the real-world, anomalous occur suddenly during the course of normal events. This is the reason that these approaches can not be applicable in the real world and produce many false positives even for normal behaviors. The boundary between normal and anomalous behaviors is very narrow and usually ambiguous. Furthermore, in the real-world, the usually same behavior can be detected as normal or anomalous behavior under different settings and environmental conditions. Therefore, we believe that training a model using normal and anomalous may help the anomalous model to learn in a better way. Therefore, in this paper, we propose a supervised solution of crowd anomalous behaviors.

In computer vision-based video surveillance, generally, human detection and tracking of people are the main preprocessing steps. The performance of any algorithm depends on the accuracy of these steps. Generally, detection and tracking require low-level appearance and motion features [24], [27] to detect humans in the crowd. These methods depend on the extraction of handcrafted appearance features. These features work well in low-density situations, where the people in the scene are sparsely distributed and most parts of human bodies are visible. Therefore, its easy for a human detector to detect the human body in low dense situations. However, the situation becomes otherwise in high-density situations. In high-density crowds, due to severe clutter, occlusions, and extremely small size of human, detector face challenges in precisely detecting humans.

With the weak performance of human detectors, as an alternative, the researchers are employing holistic methods by adopting optical flow that exploits global motion information. Optical flow is a low-level motion feature and computed densely for each pixel of the image. We observed that optical flow performs well in high-density crowds that involves unique motion patterns. This approach has been widely adopted by different researchers [1], [2], [18]. The main advantage of this approach is that it does not depend on detection and tracking rather it computes the motion vector of every pixel. We can utilize this information and extracts trajectories level information using the particle advection approach. The particle advection approach is adopted in different crowd analysis problems. First, the approach is adopted by Saad et al. in [1] for crowd flow segmentation and stability analysis. Mehran et al. [18] adopt this approach for anomaly detection and Solmaz et al. [23] use for identifying different behaviors in the crowd. The approach in [2] utilizes the motion of the crowd to handle target tracking. Sultan et al. [13] adopt an approach for distinguishing main motion flows in a crowd scene and predict the source and sink of the crowd.

In this paper, we propose a model that fuses novel feature descriptors to detect anomaly in challenging situations. We argue that anomaly can be modeled from trajectory information. We first compute optical flow and then extract point trajectories by initializing a dynamical system based on optical flow. Time integration of the dynamical system produces point trajectories. We then compute novel feature descriptors, i.e., density, shape, mean, standard deviation, and Shannon entropy from extracted trajectories. We then employ a mean-shift clustering algorithm to cluster trajectories related to anomalous behavior.

2 RELATED WORK

Detection of Anomalous behavior in video sequences is a challenging problem and have been the focus of many researchers [28], [4], [16], [7], Several approaches focused on detecting aggression [5], panic [14], and violence [19] in videos. Human violence behavior is detected by Datta et al. by using the motion of limbs and orientation of motion information. Kooij et al. fuse data from audio and video to detect aggressive behavior in videos. Gao et al. detect violent behavior by using motion-based descriptors. Mohammadi et al.[30] classify violent and non-violent behaviors by proposing new behavior heuristics. Basharat et al. move a step forward and adopt tracking to classify the normal flow of the crowd and classify deviation from the normal behavior as an anomaly. However, there are difficulties in achieving accurate and reliable trajectories.

Several methods have been proposed that avoid tracking and learn a holistic motion pattern based on histograms of optical flow [22]. In other work, social force models [18], dynamic textures mixture model [5], Hidden Markov Model (HMM) are adopted to classify anomalous behaviors. These methods learn normal behavior based on the data provided. These approaches then classify anomalous behavior if the pattern deviates from the normal patterns.

With the tremendous success of sparse feature representation and learning of visual words and dictionary, the work [30] used to learn the dictionary of normal behaviors. During the testing stage, the motion patterns are reconstructed and patterns that produce high error are classified as anomalous behaviors. With the success of deep learning models in the field of object detection, classification, and segmentation tasks, several methods have been proposed action classification in videos [11]. However, a deep learning network requires a huge amount of annotated data to learn the representation effectively. This becomes a bottleneck for deep learning models. Currently, methods [7] employed deep learning autoencoders to learn normal behaviors and use reconstruction error to detect anomalous behavior. Joachims et al. [9] proposed an approach based on rank-Support Vector Machine (SVM) to improve the content retrieval process from the web. Bergeron et al. [8] proposed an approach based on linear programming to deal with various ranking problems. Several other methods mainly focus on simple specific behavior patterns in a crowd scene. However, most of these methods do not work in real-time applications and require a large amount of training data. These methods include detecting normal and abnormal interactions [17], group interactions [20]. Several methods are proposed for crowd analysis [21]. However, these methods require offline learning that requires a large amount of data. This is the reason that these methods cannot be in real-time interactive applications. Other approaches focus on low-density crowds and employ tracking data to learn behavior representation [26] proposed a method that classifies the scene into main and background agents.

3 PROPOSED METHODOLOGY

The proposed approach starts by extracting motion information from the crowded videos. We extract motion information by using trajectories since trajectories capture the complex spatial-temporal information in videos. Therefore, we model the problem of anomaly detection in terms of trajectory extraction. After extracting trajectories, we then compute multiple features on the top of trajectories and then fuse features. These fused features are learned through a support vector machine that best learns the representation of anomalous and normal trajectories. Generally, our method follows the following pipeline.

(1) Extracting trajectories. (2) Trajectory clustering. (3) Computing multiple features. (4) Fusion of features followed by classification.

3.1 TRAJECTORIES EXTRACTION

In this section, we discuss the methodology of extracting trajectories from the video scene. It is to be noted that in high-density situations, state-of-the-art object detector and tracker are in-efficient to extract trajectories. It attributes to the extremely small size of human heads, occlusion, and severs clutter in the scene. Therefore, in densely crowded situations, we cannot employ existing object detectors and trackers. To address this problem, in this paper, we adopt a holistic approach and extract trajectories by using a point tracker, i.e., Lucas-Kanade tracker. Lucas-Kanade tracker first extracts reliable features, i.e., edges and corner points, and track these features through multiple frames and in multiple scales by adopting a pyramidal approach. We first extract edge points using the Harris corner detector. Each corner point is then tracked through multiple frames via the Lucas-Kanade tracker.

As in videos, new objects appear in the subsequent frames of the video with the passage of time. Therefore, we sample new points after every 10th frame of the video and add to the tracker. The trajectories where the distance between the starting point and endpoints is less than a specified threshold are regarded as stationary trajectories and are removed to speed up the process.

3.2 FEATURE EXTRACTION

After trajectories obtained from the previous process, we now extract multiple features from the trajectories. The features include shape, density, structural and motion features.

3.2.1 SPATIAL-TEMPORAL SHAPE

Every trajectory corresponding to a person follows a shape that provides important cue about the current behavior in the scene. Therefore, to extract the spatiotemporal shape of the trajectory, we model each trajectory as a polynomial function as

$$\mathrm{i(t)} = x_0 + x_1 t + x_2 t^2 + x_3 t^3 \quad (1),$$

$$\mathrm{j(t)} = y_0 + y_1 t + y_2 t^2 + y_3 t^3 \quad (2),$$

where i and j represent spatial coordinates of trajectory corresponds to the horizontal and vertical axis. It is given the value to t = {1, L}, where L is computed as the absolute difference between the start and endpoint of the trajectory. Symbols x and y are the coefficients and computed separately for i and j. From the above equation, we compute the shape of the trajectory as

$$\mathrm{F}_{\text{shape}} = [\, x_0, \dots \dots x_3, y_0, \dots \dots y_3] \quad (3).$$

3.2.2 DENSITY

Density provides important cue about the current behavior in the scene. High density in crowded scenes indicates a potential anomaly in the scene. Therefore, for anomaly detection, we also incorporate density information. We compute the density by clustering nearby trajectories, where the spatial similarity is measured by the Longest Common Sub Sequence (LCSS).

The major task of LCSS is to find trajectories considering the spatial location. The trajectories near to the analyzed one will be clustered together. We apply the following process to cluster similar trajectories. It is to be noted that similar trajectories are spatially close trajectories. Let T_a and T_b represent two trajectories and the length of trajectories are s1 and s2 respectively. We compute spatial proximity by recursively matching the spatial proximity of M points of both trajectories. Here, we define two parameters that control the matching criteria. Generally, the matching value represents the density Fdensity and computed as

$$F_{density} = \begin{cases} 0, & \text{if } x = 0 \text{ or } y = 0 \\ 1, & \text{if } |T_a(x) - T_b(y)|_2 < w \end{cases} \quad (4).$$

The spatial correspondence between two trajectory T_a and T_b is computed as $similarity\ (T_a, T_b) = \frac{LCS(T_a,T_b)}{\min(S_1,S_2)}$, where quotient term represents the total number of points matched (spatially closed) between T_a and T_b.

3.2.3 STRUCTURAL AND MOTION FEATURES

After obtaining dense, long, and reliable trajectories, the next step is to compute descriptors that encode the motion and structural information of the trajectories. But before computing descriptors, we encode local motion patterns from trajectories by computing the shape of the trajectory. Consider a trajectory of length L, we describe its shape by a set of displacement vectors as $\Delta P_t \dots . \Delta P_{(t+L-1)}$, where ΔP_t is a displacement and computed as $\Delta P_t = (P_{t+1} - P_t)$. We normalize the resultant vector by the sum of magnitude as

$$F_{sm} = \frac{\Delta P_t \dots \Delta P_{(t+L-1)}}{b} \quad (5).$$

3.2.4 FEATURE FUSION

After extracting multiple features from trajectories, we then fuse the features for the training process. During training, for every video, we keep 60% frames for training and the rest for validation. We adopt temporal patch wise training, we divide each input video sequence into overlapping temporal windows. we keep the overlapping ratio as 0.4. The pipeline of extracting trajectories is shown in Figure 1. We then extract motion trajectories and compute features from each temporal segment. The features from each segment are then concatenated together as $F_{shape}, F_{density}, F_{sm}$.

(a) (b) (c)

Figure 1: (a) the sample frame, (b) the trajectories extracted overlaid over the image and (c) the density map.

4 DETECTION OF ANOMALY

Based on the features extracted, anomaly detection can be performed. We observed that high density crowded scenes exhibit dominant motion patterns. These dominant motion patterns can be clustered and analyzed further for anomaly detection. The trajectories belong to anomaly may be assigned to any of the clusters and in some cases can not show the highest degree of similarity with any of the clusters. Therefore, to precisely detect and cluster trajectories that actually belong to the anomaly, we use Shannon Entropy [29] that describes the whole feature space (computed in the previous section) into a value. The higher value indicates that the trajectory belongs to anomalous behavior while the lower value represents trajectory belonging to a normal situation. Therefore, in contrast to previous methods that compute the distance between two cluster centers, we compute probability distribution between the mid-point of each trajectory to the mean of each cluster. We then compute the entropy of this distribution and define a threshold value. If the entropy value is greater than the predefined threshold value, the trajectory will be classified as anomalous while the trajectory lower than the threshold value will be labeled as normal. We experimentally compute the value of threshold Ψ using cross-validation. From empirical evidence, we observe that the attributes of high-density crowds change frequently. For example, one segment of the crowd exhibiting a specific behavior can suddenly change the behavior, and in this way, the characteristics of the trajectories change. Furthermore, new trajectories that are added after a predefined interval of time can exhibit similar behavior and produce similar features as one of the clusters but it may exhibit different behavior due to their late injection. To address this, we adopt a voting scheme that continuously votes (either positive or negative) to those trajectories classified as anomalous. In this way, we analyze and check anomalous trajectories for a longer duration and we discard those trajectories with negative votes

5 EXPERIMENT RESULTS

In this section, we evaluate and compare the proposed approach with other state-of-the-art methods in both quantitative and qualitative ways. For rigorous evaluation, we used two publicly available datasets, i.e., [12] and UCF [18]. Dataset [12] is initially proposed by sultan et al. and it contains 16 videos collected from different sources. The videos cover different crowd densities and anomalies. For example, the airport sequence from the dataset shows the scenario of the airport, where the people are moving in different directions using elevators. This video contains normal behavior of the crowd and covers low to medium crowd density. station sequence shows the platform of the train station, where the people moving from different directions gathered at a single point, thus increasing the density that causes clogging and congestion.

In the same way, UCF dataset [18] consists of video sequences, that cover different scenarios of crowd escape from three different indoor and outdoor environments. The initial part of each video sequence covers the normal behavior of the crowd while abnormal behavior is exhibited by the crowd at the end of the video sequence. In this way, in a single video sequence, we have both normal and abnormal behaviors and we evaluate the robustness of the proposed method on these datasets.

Table 1: Performance of the proposed method on different video sequences from [12] dataset.

Video Sequences	Precision	Recall	F-Score
Station 1	0.82	0.94	0.88
Station 2	0.84	0.87	0.85
Penn Station	0.89	0.94	0.91
Seq 30	0.81	0.87	0.84
Hseq01	0.90	0.87	0.88
Hseq02	0.93	0.89	0.91
Hseq03	0.91	0.83	0.87
Hseq04	0.89	0.93	0.91
Concert	0.83	0.9	0.86

To evaluate the effectiveness of the proposed approach, we first extract trajectories from each input video sequence. We then compute the features from each trajectory and classify trajectories into two classes, i.e., anomalous/normal trajectories. Since we are using video sequences, we also annotate the anomalous and normal trajectories in the original video. We report the results of the proposed approach on these two datasets in Table 1. From the table, it is obvious that the proposed method achieves high performance on classifying trajectories. However, the specificity of classifying the normal trajectories is lower than classifying abnormal trajectories. We observed that low performance is due to fact that the model is trained on a large number of anomalous trajectories than normal trajectories. We improve the specificity of the proposed approach for classifying the normal trajectories by providing more data by adopting the method of data augmentation. We observe that our proposed method precisely classifies the anomalous trajectories with high accuracy. Figure 2 shows the subway station video sequence, where the people from multiple entrances gathered to exit from a single door. We first extract trajectories from the whole video sequence as shown in Figure 2(b). We encoded trajectories with different colors to represent that trajectories belong to different pedestrians of the crowd. We then compute features for each trajectory and classify each trajectory into normal/abnormal. Figure 2(c) shows the abnormal trajectories encoded in red color. From the figure, it is obvious that our proposed method precisely classifies trajectories. We then adopt a clustering algorithm that cluster abnormal regions as indicated in Figure 2(d).

Table 2: Comparison of different methods

Methods	Precision	Recall	F-Score
Guo et al. [6]	0.72	0.65	0.7
Mehran et al. [18]	0.84	0.82	0.83
Biswas et al. [3]	0.78	0.57	0.66
Proposed	0.87	0.84	0.85

By closely analyzing the video sequence, the trajectories belong to the clogging crowd in the subway represent the congestion behavior, where the pedestrian could not move smoothly and exhibit to and fro motion to maintain the balance.

We also compare the performance of the proposed method with other existing methods in Table 2. From the table, it is obvious that our proposed method supersedes other state-of-the-art methods by a great margin. The work [6] could not perform well since the method relies on computing speed features to analyze the trajectory. The work [3] adopts an unsupervised approach to detect hierarchical features to detect anomalous trajectory.

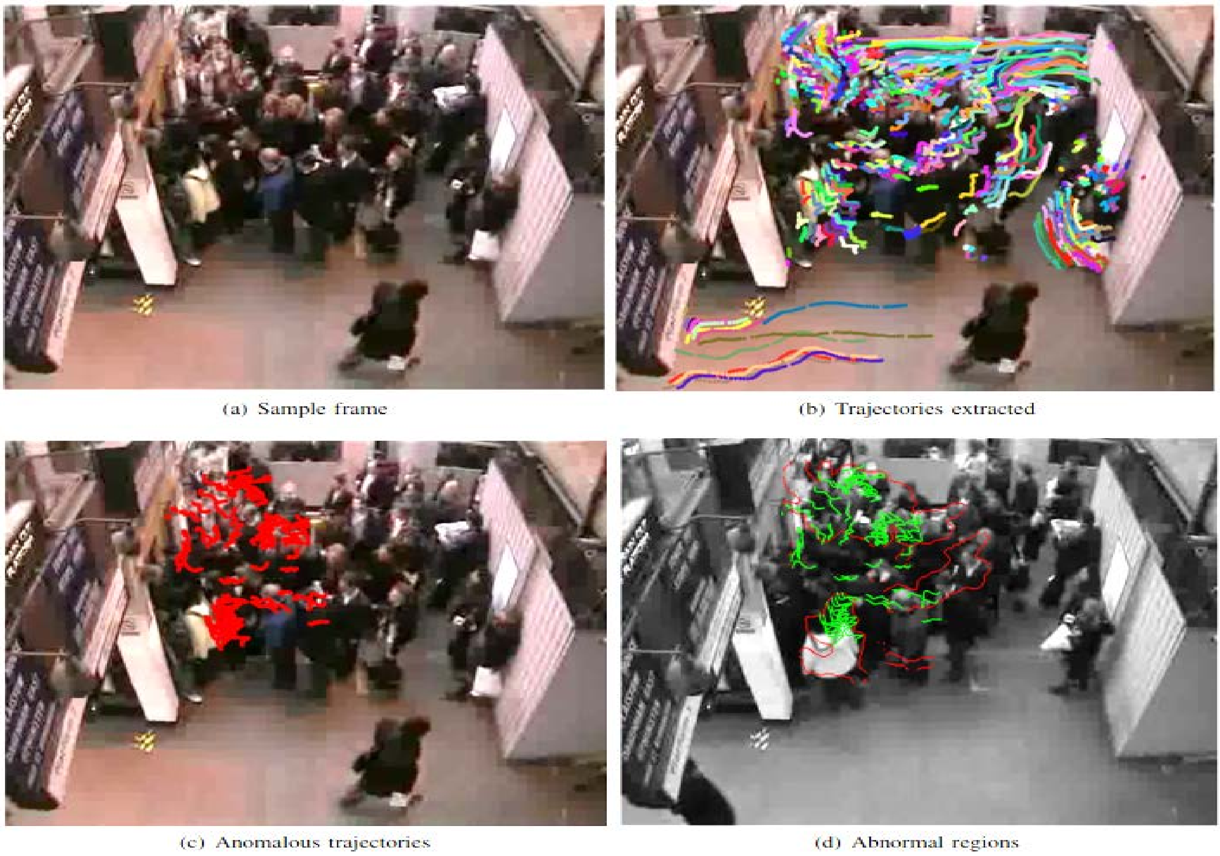

Figure 2: Visualization of abnormal trajectories detection, (a) the sample frame, (b) the trajectories overlaid on the image, (c) abnormal trajectories, and (d) the abnormal locations.

6 CONCLUSION

In this paper, we proposed a novel approach that performs trajectory level analysis to detect anomalous regions in the scene. The method first extracts trajectories from videos and then compute different features from trajectories. After classifying trajectories, we then cluster trajectories that will indicate anomalous regions. From this study, we observe the use of multiple features for determining anomalous trajectories. Furthermore, the anomalous trajectory exhibits similar behavior belong to dominant motion patterns but significantly different in other aspects. Finally, the proposed work will lead to the improvement of surveillance methods in public places and mass events.

7 AVAILABILITY OF DATA AND MATERIAL

Information can be made available by contacting the corresponding author.

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