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Global Abnormal Event Detection in Video via Motion Information Entropy

Zhipeng Wang(1), Chunping Hou (1), Beichen Li*(1) ,
Tianyu Chen(2) , Li Yao(3) ,Mei Song(4)
(1) School of Electrical and Information Engineering, Tianjin University, Tianjin, China, 300072
(2) International Engineering Institute, Tianjin University, Tianjin, China, 300072
(2) College of Information Science and Technology, Beijing Normal University, Beijing, China, 100875
(3) School of Electronic Engineering, Beijing University of Posts and Telecommunication, Beijing, China, 100876

Abstract

Abnormal event detection is a rapid development task in video analysis, which is aimed to distinguish abnormal and normal events in surveillance videos. As the normal and abnormal events have some similarities, more discriminating methods or motion information need to be explored. In this paper, to detect escaping people in different scenes, a global abnormal event detection method is proposed based on motion information entropy. To be specific, the proposed method utilizes the directions and magnitudes of motion vectors extracted from optical flow field to calculate the motion information entropy which represents the uncertainty of motion information. The normal samples are distributed around the center of a Gaussian distribution while the abnormal ones are distributed on the side. Experimental result shows that the proposed method has better detection performance than most of other classic methods with much lower computational complexity.

1. Introduction

Video abnormal event detection enables to capture the location of abnormal event in continuous frames. In the past decade, this task has been a booming research topic and has benefited various applications such as intelligent surveillance, social security system[1].

Anomaly detection aims to distinguish the normal patterns and abnormal patterns. In various kinds of patterns, such as colour, texture and boundary, motion pattern has typical ability to detect abnormal event since the difference between normality and abnormality motion patterns is distinct and interpretable. To date, many methods mention motion patterns and subsequently achieve satisfied performance. Unfortunately, most of them are too complex, thus these methods are inappropriate for low-power consumption environment. In addition, most existing methods were designed to cope with particular scenes and lacked of generalization.

This paper focuses on global abnormality detection in the crowd, which is different from local abnormality[2],[3] . Local abnormality just means special event in crowd scenes such as wheelchairs, bicycles etc. Global abnormality detection is more suitable for crowd scenes since global abnormality (which usually means that a serious event has been occurred in current scene) is more important than local one. Furthermore, in crowd scenes, when abnormality occurs, the region of abnormal event influenced couldn't be too local. Hence, global abnormality analysis is valuable enough and develop rapidly. For global abnormal event, we can hypothesize that motion of each pedestrian is motivation aimlessly or individually. Therefore, the motion patterns are irregular and confusing. When abnormality occurs, the pedestrians have similarity motivation to escape the scene. In addition, each scene has particular structure such as the location of exit, direction of road. Hence, motion patterns tend to be similar when global abnormality happens in crowd scene.

Considering the difference of motion patterns in normal situation and abnormal situation, we use a novel method to describe the confusion of scene called motion information entropy. Different from the previous works, a new method to calculate motion entropy is proposed which emphasize a whole frame's motion information. Our method is sufficient simple to operate in different processors, so some problems can be solved easily, for example perspective distortion.

We evaluate the proposed method on UMN dataset which has three unequal scenes. The proposed method has following contributions: a new method to measure the degree of scene confusion is proposed. In addition, we propose a more reasonable way to detect the abnormal event through Gaussian distribution. While the motion information is located in the side of the distribution, it can be detected as abnormal event.

2. Methodogy

The proposed method of global abnormal detection consists of two components. The first calculates frame-level motion entropy which is used to describe the confusion of scene. Based on the motion entropy, the second component to fit a Gaussian distribution of normal scene adopt truncated probability to detect whether this frame is abnormal or not. The architecture of whole method is illustrated in Figure. 1.

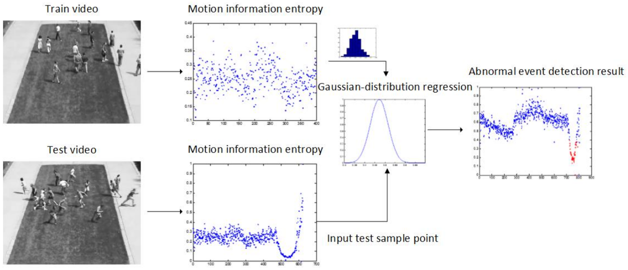


Figure 1. Overview of proposed global abnormal event detection based on motion information entropy.

Shannon information entropy describing the degree of system stability has extensive application in different fields, such as radio signal processing, image processing and electromagnetics in biology and medicine. For video abnormal detection, a series of frames can be regarded as a continuous system including motion information. For this instance, based on Shannon information entropy, motion entropy is used to represent the chaos of current scene. When globally abnormal event occurs, the information of motion system tends to be stable because of the characteristic in scene structure. While the motion entropy reduces dramatically, the normal frame and the abnormal frame can be distinguished immediately.

Given each input video frame F_t, its motion filed MF_t is calculated using LK optical flow with respect to the previous frame F_{t-1}. In order to obtain motion entropy, each pixel-level motion vector is quantified to 16 ranges:

$$2\pi \cdot \frac{b-1}{l} \le \theta < 2\pi \cdot \frac{b}{l} \quad b = 1,2,...,16 \qquad (1).$$

Where b denotes each quantizing interval, l denotes quantization levels, which is empirically set to be 16, and θ is the direction angle of motion vector:

$$\theta = \tan^{-1}\left(\frac{v}{h}\right) \qquad (2).$$

Here, v and h respectively denote the horizontal and vertical components of pixel-level optical flow vector.

We propose motion entropy to detect abnormal event, which describes the distribution of each vector of different directions. Following this motivation, motion information of each direction interval is weighted according to the magnitude proportion of this component. Hence, the motion entropy can be formulated as:

$$E = \sum_k MagWeight_k \cdot Entropy_k \qquad (3).$$

where k is associated with the index of each direction interval and *Entropyk* is the entropy of each direction interval with each pixel of current frame considered, just like the following form:

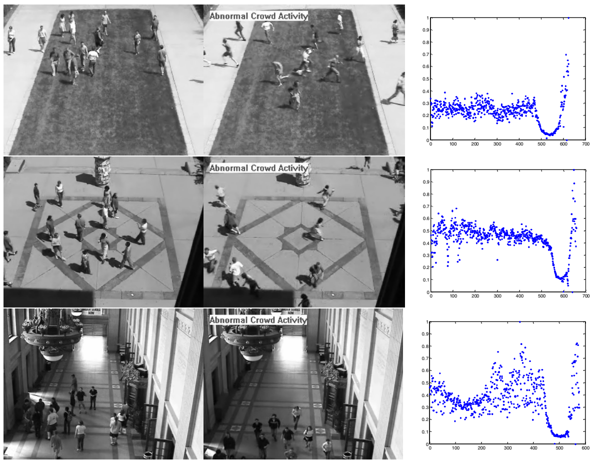
$$Engropy_k = -p_k \cdot \log\left(p_k\right) \qquad (5).$$

Here, p_k is the probability of motion vector located in kth direction interval in current frame.

Supposing $MagWeight_k$ donates the weight of corresponding direction interval, which is calculated through the component of kth direction interval in all motion vectors. It can be formulated as:

$$MagWeight_k = \frac{Magnitude_k}{\sum_k Magnitude_k} \qquad (6).$$

Obviously, the underlying rationally of the Eq.3 is echoed in two aspects. First, both magnitude and direction information can be integrated to represent the scene. Second, the value of the entropy is used to measure the chaos of the scene. When scene is confused, with larger value, usually imply that the scene is normal, and the small value means abnormal situation. The motion entropy is evaluated at each frame of video batch, and is then normalized to the range of [0,1]. The result is shown in Figure. 2.



(a)normal (b)abnormal (c)entropy

Figure 2. Motion information entropy distribution in different scenes (a) normal behavior, (b) abnormal behavior, (c) the distribution of motion information entropy

From the perspective of motion entropy, although motion entropy can distinguish the normal and abnormal event obviously, the reasonable threshold is a hard problem. Different from the conventional method, to set a fixed entropy value, we use a more reasonable method based on Gussian-Distribution regression and set a feasible truncated probability.

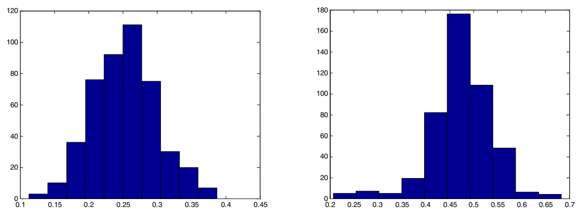


Figure 3. The distribution of motion information entropy in normal situation.

Following this notion, according to the distribution of motion entropy in training set as shown in Figure. 3, we can find that most of the motion entropy distribute in the middle of the histogram but some of that are outliers. Hence, in order to exclude outliers and furthermore reserve as much as samples, we set 98 percent of samples to be saved ,and 1 percent of minimum samples and 1 percent of maximum samples are excluded.

Specifically, after the outliers are excluded, it is suitable that the distribution of motion entropy can be regressed by Gaussian distribution. Following normal distribution, μ and σ separately denote mean value and variance of normal distribution, we adopt maximum likelihood method to estimate the parameter of training set(Eq. 8).

$$f(x;\mu,\sigma)=\frac{1}{\sigma\sqrt{2\pi}}\exp\left(-\frac{(x-\mu)^2}{2\sigma^2}\right) \quad (7).$$

$$\mu=\frac{1}{n}\sum_i X_i \quad \sigma^2=\frac{1}{n}\sum_i X_i^2-\left(\frac{1}{n}\sum_i X_i\right)^2 \quad (8).$$

After the motion entropy distribution is regressed, we can find that the probability density curve is tight enough. Meanwhile, this regression curve is more suitable to describe normal motion entropy distribution. Thus, based on the model of normal event entropy distribution established, the globally abnormal event detection becomes a confidence intervals estimation problem. Through the truncated probability estimated, we can find the motion entropy of current frame locating in interval $[\mu - a, \mu + a]$ is normal. While the motion entropy absence in this interval, it is abnormal, as shown in Figure. 4.

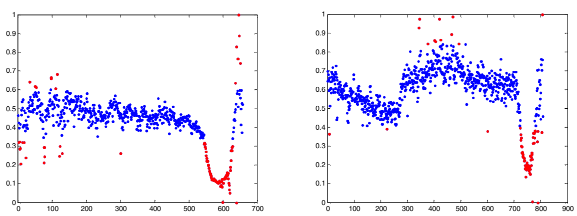
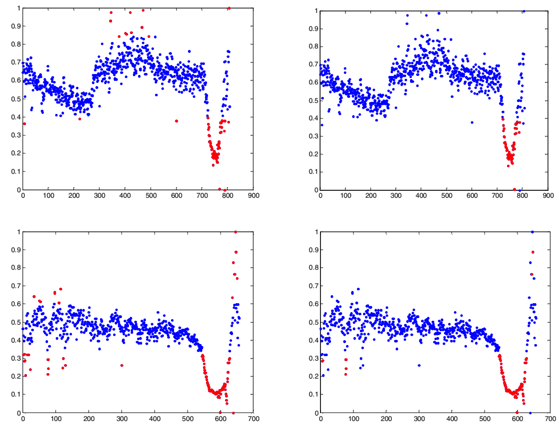


Figure 4. The distribution of testing set samples (Blue: normal, Red: abnormal).

Specially, the video temporal compaction should be considered, abnormal event couldn't appear in single frame. No matter normal frames or abnormal frames should be continuous. Thus, to solve this problem, a frame is labeled as abnormal frame only if forward three frames or backward three frames are totally abnormal. After such processing, the quantitative proofs can be found in Figure. 5.



(a) (b)

Figure 5. (a)The result diagram without video compaction processing. (b)The result diagram through video compaction processing.

3. Results and discussions

We quantitatively evaluate the performance of our method over UMN database, which contains globally abnormal events in three different scenes. The frame number of three scenes is 1453, 4143 and 2143 and separately has 200, 615, 160 abnormal frames.

For globally abnormal detection task, we merely want to know which frame occurs abnormal event. Hence, frame-level area under the curve(AUC) and equal error rate (EER) are adopted to measure each method's performance. Figure 6 shows the effect of proposed method and Figure 7 and Table 1, separately, show the receiver operating characteristic (ROC) result and the performance.

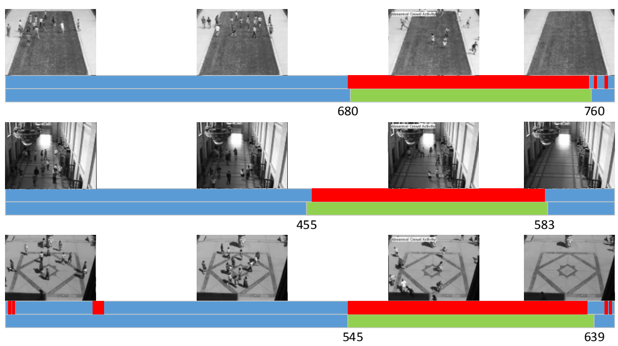


Figure 6. The effect of three different scenes.(the red strip means test result and the green one is the groundtruth).

In figure 6, the blue range denotes the training frames, the green range denotes the groundtruth and the red one means the result of proposed method. Hence, we can directly find that the proposed method can detect global abnormal event exactly and mark most of the abnormal frames with little frames false and negative.

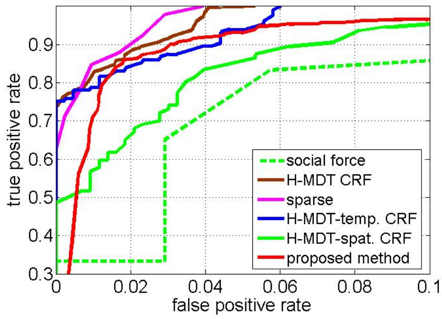


Figure 7. The frame-level ROC curves for UMN database.

In figure 7, we show the frame-level ROC curves on the UMN database. The result shows the proposed method is effective in different scenes with various scene structures, and we can find that our method achieves comparable result of state-of-the-art methods through comparing the area under ROC curves of different methods[4]-[8].

Table 1. comparison of the frame-level AUC and EER rate on the UMN database.

Method	AUC	EER
proposed	97.9%	5.3%
Social force model	94.9%	12.6%
Sparse	99.6%	2.8%
HOS-HOG	98.1%	5.6%
H-MDT-spat.CRF	97.9%	7.8%
H-MDT CRF	99.5%	3.7%

In table 1, we show the comparison of the frame-level AUC and EER rate with different method. In addition, we can find that our method has comparable detection performance than some of state-of-the-art methods in low algorithm complexity situation.

4. Conclusions

In this paper we proposed a method to detect global abnormal events. Motion information entropy is exploited to describe the crowd motion pattern. In our method, we learned a normal situation entropy distribution and adopted a Gaussian regression to measure this distribution. Finally, the truncated probability is used to detect the normal event or not. Since our method refine enough, it can be used in various hardware environments. Experiment result shows that the proposed method is effective in different scenes and has a well performance. Our future work will focus on optimizing the proposed method to be effective in the luminance changing environment and utilize a more reasonable theory, Extreme Value Theory, to describe the abnormal event information entropy distribution.

5. Acknowledgments

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6. References

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