Crowd Motion Monitoring with Thermodynamics-Inspired Feature

Xinfeng Zhang[1], Su Yang[*1], Yuan Yan Tang[2], Weishan Zhang[3]
[1]Shanghai Key Laboratory of Intelligent Information Processing, College of Computer Science, Fudan University, Shanghai 201203, China
[2]Department of Computer and Information Science, University of Macau, Macau, China
[3]Department of Software Engineering, China University of Petroleum, Qingdao 266580, China
10110240026@fudan.edu.cn, suyang@fudan.edu.cn, yytang@umac.mo, zhangws@upc.edu.cn

Abstract

Crowd motion in surveillance videos is comparable to heat motion of basic particles. Inspired by that, we introduce Boltzmann Entropy to measure crowd motion in optical flow field so as to detect abnormal collective behaviors. As a result, the collective crowd moving pattern can be represented as a time series. We found that when most people behave anomaly, the entropy value will increase drastically. Thus, a threshold can be applied to the time series to identify abnormal crowd commotion in a simple and efficient manner without machine learning. The experimental results show promising performance compared with the state of the art methods. The system works in real time with high precision.

Introduction

Crowd commotion can act as signals to warn emergent events such as natural disasters or terroristic attacks as these should cause people to behave abnormally. Here, the key issue for crowd motion monitoring is how to model crowd motion to reflect different motion patterns. Traditional methods treat every person as an individual object to perform subsequent analysis. However, object detection and tracking is impractical in crowded scenes due to the high-density of people. Recently, the trend is shifted to model people's collective motion at particle level, namely, pixels, image patches, or local 3D cuboids. The fundamental to render particle-level analysis is the so-called optical flow technique, which results in a motion vector field to figure out the moving trend of every particle. Then, people's global motion pattern can be summarized statistically from the local movements of particles. The state of the art methods fall into 3 categories: property, interaction, and trajectory-based approaches. For particle property-based approaches, Mahadevan et al. employ a mixture of dynamic textures to represent jointly the appearance and dynamics of local portions of videos of crowded scenes (Mahadevan et al. 2010). This approach performs well at the cost of big computational load. For particle interaction-based approaches, the representative is the Social Force Model (SFM) (Mehran, Oyama and Shah 2009), where group actions are modeled as interaction forces of subjects computed from optical flows. However, the computation of interaction forces is in general error-prone. The Particle Swarm Optimization (PSO) method (Raghavendra et al. 2011) is robust in optimizing the interaction forces computed from SFM but is not applicable to online surveillance due to the time-consuming optimization. For particle trajectory-based approaches, Wu et al. (Wu, Moore and Shah 2010) use chaotic invariants of Lagrangian particle trajectories, which are known as maximal Lyapunov exponent and correlation dimension, to detect and localize anomalies in crowded scenes. When the object motion is spatially constrained such as in corridor or underpass, however, the task becomes extremely difficult for such methods.

Most of the aforementioned methods require a machine learning process, which is time-consuming while the performance is subject to training examples. To overcome such drawbacks, some learning-free approaches are proposed, for which decision-making is based on watching whether the target feature value exceeds a predefined threshold. Susan et al. (Susan and Hanmandlu 2013) adopt the non-extensive entropy to characterize crowd motion, which is a variant of Shannon Entropy (Shannon 1948). However, this feature is not reasonable in that it concerns only the probability of particle distribution but misses the total amount of subjects involved in crowd motion, which is subject to local perturbation.

*Corresponding author: Su Yang (This work is supported by NSFC under grant No. 61472087 and 973 program under grant No. 2010CB731401)

The Boltzmann Entropy to Feature Crowd Motion for Anomaly Detection

The present features are not robust enough as they do not reflect the physical nature of crowd motion. Intuitively, crowd motion in surveillance videos is comparable to heat motion of basic particles such as molecules in terms of thermodynamics. Inspired by Boltzmann Entropy (Halliday, Resnick and Walker 2010), we apply it to measure the spatio-temporal motion of particles following optical flow computation. As shown in Figure 1, when abnormal crowd movement occurs, Boltzmann Entropy will increase drastically. Accordingly, anomaly can be alarmed as low-probability event of rarely appeared big increment of Boltzmann Entropy, where we employ Gaussian model for decision-making and machine learning is not needed.

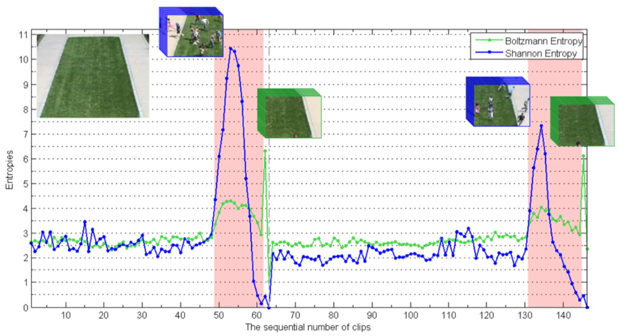

Figure 1. Time series of entropy values against video clips (Blue one: Boltzmann Entropy; Green one: Shannon Entropy). The shadows show the lasting time of crowd commotion. The online monitoring images attached to the peaks of the corresponding curves show that Boltzmann Entropy is more reasonable.

Experiments

With UMN data (http://mha.cs.umn.edu/movies/crowd-activity-all.avi), a comparison of our method with Non-extensive Entropy (Susan and Hanmandlu 2013), Sparse Reconstruction Cost method (Yang, Junsong and Ji 2011), Particle Swarm Optimization based Social Force Model (PSO-SFM) (Raghavendra et al. 2011), Social Force Model (Mehran, Oyama and Shah 2009), and Optical Flow methods (Andrade, Blunsden and Fisher 2006) is done in terms of both the averaged AUC (area under ROC curve) and the speed. It is shown in Table 1 that our method outperforms all the methods except the PSO-SFM but the speed of PSO-SFM is much slower than ours. This makes PSO-SFM impractical for online monitoring but our method works.

Table 2 shows the confusion matrix in identifying normal and abnormal behaviors on UMN and PETS2009 S3 dataset (http://www.cvg.rdg.ac.uk/PETS2009). The false alarm and missing rate is 6.68% and 5.05%, respectively. The performance is high.

Table 1. Comparison of the proposed method to the baseline methods (Entropy: Non-extensive Entropy; Sparse: Sparse Reconstruction Cost: PSO: PSO-SFM; OF: Optical Flow)

Methods	Ours	Entropy	Sparse	PSO	SFM	OF
AUC	0.985	0.95	0.978	0.996	0.96	0.84
Speed (fps)	5	4	<1	<<1	3	5

Table 2. The confusion matrix (%)

Events	Normal	Abnormal
Normal	93.32	6.68
Abnormal	5.05	94.95

Conclusion

We introduce Boltzmann Entropy to capture the chaos degree of crowd behavior for video surveillance. It is extracted from optical flow directly without the need to detect or track objects individually. As the crowd motion is represent as a single time series, only a threshold is needed for decision making, which is free of machine learning. Its high-speed computation enables real-time monitoring.

References

Andrade, E. L., Blunsden, S. and Fisher, R. B. 2006. Modelling crowd scenes for event detection. In *Proceedings of the Pattern Recognition, 2006. ICPR 2006. 18th International Conference on*, 175-178.

Halliday, D., Resnick, R. and Walker, J. 2010. Fundamentals of physics extended 9 edition. *Wiley*: 550-560

Mahadevan, V., Weixin, L., Bhalodia, V. and Vasconcelos, N. 2010. Anomaly detection in crowded scenes. In *Proceedings of the Computer Vision and Pattern Recognition (CVPR), 2010 IEEE Conference on*, 1975-1981.

Mehran, R., Oyama, A. and Shah, M. 2009. Abnormal crowd behavior detection using social force model. In *Proceedings of the Computer Vision and Pattern Recognition, 2009. CVPR 2009. IEEE Conference on*, 935-942.

Raghavendra, R., Del Bue, A., Cristani, M. and Murino, V. 2011. Optimizing interaction force for global anomaly detection in crowded scenes. In *Proceedings of the Computer Vision Workshops (ICCV Workshops), 2011 IEEE International Conference on*, 136-143.

Shannon, C. E. 1948. A mathematical theory of communication. *Bell System Technical Journal*, 27: 379-423.27.

Susan, S. and Hanmandlu, M. 2013. Unsupervised detection of nonlinearity in motion using weighted average of non-extensive entropies. *Signal, Image and Video Processing*: 1-15

Wu, S., Moore, B. E. and Shah, M. 2010. Chaotic invariants of lagrangian particle trajectories for anomaly detection in crowded scenes. In *Proceedings of the Computer Vision and Pattern Recognition (CVPR), 2010 IEEE Conference on*, 2054-2060.

Yang, C., Junsong, Y. and Ji, L. 2011. Sparse reconstruction cost for abnormal event detection. In *Proceedings of the Computer Vision and Pattern Recognition (CVPR), 2011 IEEE Conference on*, 3449-3456.