Crowd Security Detection based on Entropy Model

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ABSTRACT

Identifying the terror attack, illegal public gathering or other mass events risks by utilizing cameras is an important concern both in crowd security area and in pattern recognition research area. This paper provides a physical entropy model to measure the crowd security level. The entropy model was created by identifying individuals' moving velocity and the related probability. The individuals are represented by Harris Corners in videos, thus to avoid the time-consuming human recognition task. Simulation experiment and video detection experiments were conducted, verified that in the disordered state, the entropy is higher; while in ordered state, the entropy is much lower; when the crowd security has a sudden change, the entropy will change. It was verified that the entropy is the applicable indicator of crowd security. By recognizing the entropy mutation, it is possible to automatically detect the abnormal crowd behavior and to set the warning alarm.

Keywords

Crowd mutation, crowd security, entropy, warning alarm

INTRODUCTION

Most crowd disasters or mass events, such as human stampede, illegal public gathering were accompanied with crowd mutations. Sometimes the crowd mutations were caused by emergency events like terror attack, explosion, sudden fire, car accidents, etc. It is quite important to detect the crowd mutation quickly and send early warning to the crowd. Since the cameras are more and more popular in public places, the sooner the cameras detect crowd mutations, the better to respond.

Statistical methods are used for the detection of abnormal motions or crowd disasters. Dirk Helbing (Helbing and Johansson, 2007) studied several physical parameters to predict the crowd disaster. X L Zhang (Zhang, Weng, Yuan and . 2013) analyzed the velocity profile during a real mass event. J Ma(Ma, Song, Lo and Fang, 2013) studied that different clusters of pedestrians displayed different velocity features in crowd-quakes. Cao (Cao, Wu, Guo, Yu and Xu, 2009) also adopt the kinetic energy to detect anomaly motions. Vijay Mahadevan (Vijay Mahadevan, 2010) proposed that temporal anomalies are equated to events of low-probability. BorislavAntic (A and B.Ommer, 2011) presented a probabilistic model that localized abnormalities using statistical inference. Louis Kratz (Louis Kratz, 2009) presented a novel statistical framework for modeling the local spatio-temporal motion pattern behavior of extremely crowded scenes. Ramin Mehran (Ramin Mehran, 2009) calculated the social force based on velocity and adopt LDA model to detect the abnormal behaviors.

In summary, the statistical methods were mainly focused on using physical parameters to predict the public moving trend and to describe the public motion, however the external artificial force was not considered in these cases, which were often and essential in mass incidents control. It is of importance to introduce the manual intervention from outside in regards to the emergency response management; however it is difficult if the crowd motions system is assumed as a close system.

Meanwhile, it is more realistic if the crowd motion system is studied as an open system. An essential physical concept in the open system description is entropy. In thermodynamics, entropy is a measure of the number of specific ways in which a thermodynamic system may be arranged, commonly understood as a measure of disorder.

According to the second law of thermodynamics the entropy of an isolated system never decreases; such systems spontaneously evolve towards thermodynamic equilibrium, configured with the maximum entropy. Systems which are not isolated may decrease in entropy. If the crowd is isolated from outside, the entropy will never decrease and lead the crowd to chaos (the most disordered motion), when crowd disasters possibly happen. If the crowd behavior system is open, which means it exchanges information or energy with outside, the entropy will decrease and lead the crowd to ordered situation. The higher entropy means the more disordered motions, and the lower entropy means the more ordered motions. According to the theory of entropy, considering crowd behavior system as a self-organizing system (one type of open system) gradually become a research direction in recent years. Crowd control from outside can lead to the crowd mutation from the disordered motion to the ordered motion, which is accompanied with entropy decrease. External influences, like terror attacks or explosion, can lead to the crowd mutation from the ordered motion to the disordered motion with increasing entropy.

Entropy was used to detect abnormal crowd behaviors these years. Xuxin Gua (XuxinGua, Cui and Zhu, 2014) provided a method to obtain the particle entropy by considering only the velocity direction. Considering the velocity magnitude is the key concept to describe particle features, the particle entropy here has more limitations to identify the whole crowd mutation. Saira (Pathan, Al-Hamadi and Michaelis, 2010) calculated the social entropy which means the uncertainty behavior not the order status of crowd and used the Support Vector Machines to detect crowd behaviors . Since no correlation has been established between entropy and ordered motion, it is hard to detect the crowd mutation by entropy only. In summary, the crowd behavior entropy that depicts the crowd motion macro state and reflects the crowd mutations was not constructed in above researches.

In 1877 Boltzmann visualized a probabilistic way to depict the entropy, in which he set up a relationship between the micro states of a system with the macro entropy. In 1948, Shannon Entropy was first introduced by Shannon in his landmark paper (E, 1948). Shannon is the first people to induct the entropy to information field.

In view of the fact that Boltzmann entropy is more suitable for the isolated system and needs large amount of calculation, it seems more feasible to construct crowd macroscopic state entropy function using the Shannon entropy mode. If the probability of crowd micro state is confirmed, then it will be able to determine the macro state of the Shannon entropy function. Although the micro expression of the state is very complex, but from the public security point of view, velocity of each individual and its probability distribution is an important physical parameter, and it is not difficult to obtain. Therefore, if the micro state from the crowd motion velocity and the probability distribution of the individual was built, then the Shannon entropy model to describe the crowd macro state will be constructed.

Crowd behaviors in crowd disasters were characterized with collective motion. Vicsek (Vicsek, 2008) proposed five fundamental types of collective motion: i) disordered (particles moving in random directions); ii) fully ordered (particles moving in the same direction); iii) rotational (within a rectangular or circular area); vi) critical (flocks of all sizes moving coherently indifferent directions, and the whole system is very sensitive to perturbations); v) quasi-long range velocity correlations (for elongated particles). In this study, the disordered and fully ordered motions were considered since they represent the two most typical statuses. The crowd mutation from disordered motion to ordered motion which were possibly caused by religion ceremony, or illegal public gathering were analyzed.

This paper attempts to use the individual velocity and its probability to represent the crowd micro state. By calculating the probability of each micro state, a method to express the crowd macro state using Shannon entropy is proposed. Thus, the criterion of crowd macro order status is developed based on the entropy. Since the Shannon entropy is the bridge between crowd micro states and macro state, the most important contribution of this paper is the constructions of crowd micro states and the calculating the probability of each micro state.

METHDOLOGY

Crowd behavior entropy model

Based on the Shannon's Information Entropy Theory (E, 1948), a crowd behavior entropy model was created to depict mass behaviors. The crowd motion is considered as a macroscopic synergetic dynamical system. A dynamic system was built using variables of state space and probability: （Ω，P，T）,

where $\Omega=\left\{Q_i; i=1,2,..,\|A\|\right\}$ is the whole state space matrix, Q_i denotes the state of I and $\|A\|$ denotes the total number of states. $A=\{a_1,a_2,...,a_{\|A\|}\}$ denotes collection of each matrix element. $P(Q_i)$ denotes the probability function of crowd in the state i. P is the probability function of crowd, and T represents the time.

Assume that the probability distribution is normalized as

$$\sum_{i=1}^{\|A\|} p(Q_i)=1 \tag{1}$$

The crowd behavior entropy S is described as:

$$\mathrm{S}(\Omega)=-\sum_{i=1}^{\|A\|} p(Q_i)\ln p(Q_i) \tag{2}$$

when $p(Q_i)$ is equal to zero, it means that the entropy in this micro state is equal to zero ($p(Q_i)\ln p(Q_i)=0$.)

Each of the N pedestrians i in the system has velocity $v_i(t)$. The magnitude of $v_i(t)$ is divided equally into $\|\mathrm{A}_m\|=\mathrm{M}$ partitions, and the direction of $v_i(t)$ is divided equally into $\|\mathrm{A}_n\|=N$ partitions. Then, $\|A\|$, the total number of state is M multiply N. And then, the Ω is the grids of M partitions and N partitions (each grid represents each state of Ω).

Barbara Krausz (Krausz and Bauckhage, 2012) depicted a 2D-histogram about motion direction and magnitude for velocity vectors, which inspires the appropriate way to calculate $P(Q_i)$.

Let $H(x,y)$ denote the counts of pedestrians with velocity in the partition x of magnitude and the partition of direction. So, the probability is:

$$P(Q_i)=\frac{H(x,y)}{N} \tag{3}$$

N is the number of pedestrians. The range of x is from 1 to M, and the range of y is from 1 to N.

The crowd behavior entropy of the whole system is the summary of all entropy in each micro state. The crowd behavior entropy is applied to determine the velocity field certainty thus leads to reliable measurement of system behaviors.

According to the reasoning of Robert (Gray, 2012) and Saira (Pathan, Al-Hamadi and Michaelis, 2010), when the value of $P(Q_i)$ in each status is same the entropy arrives the maximum value and the maximum value is

$$S_{max}(\Omega)=\ln\|A\| \tag{4}$$

$P(Q_i)$ is same in each state means that the velocity magnitude and direction is distributed evenly in each grid. In that case, the motion is disordered. So, literally, the entropy here can represent the ordered and disordered status of crowd motion.

Let middle valued of the entropy (for example blue line in the figure 2(c)) is set as the threshold line to distinguish ordered and disordered motion. When the entropy is higher than the threshold, the motion is disordered motion; and when the entropy is lower than the threshold, the motion is ordered motion.

Video Tracking

OpenCV software (Stavens, 2007) is the development kit to analyze the videos. Figure 1(a) shows an overview of method to obtain entropy from videos. For given input video clip, each frame was tracked to detect the corners using Harris corner detection algorithm (Harris and Stephens, 1988) A corner(J and Tomasi, 1994) can be defined as the intersection of two edges. Corner detection is an approach used within computer vision systems to extract certain kinds of features and infer the contents of an image. The corner is hardly influenced by the light condition because of its rotation invariance, which is the reason to choose Harris corner detection algorithm in this paper.

Then, Lucas-Kanade Optical Flow algorithm (Bouguet, 2001) was adopted to track the corners. Optical flow (Stavens, 2007) is the pattern of apparent motion of objects, surfaces, and edges in a visual scene caused by the relative motion between an observer (an eye or a camera) and the scene. The concept of optical flow was introduced by the American psychologist James J. Gibson in the 1940s to describe the visual stimulus provided to animals moving through the world. There are sparse optical flow and dense optical flow. The dense optical flow needs large amount of calculation, which is the reason to choose the sparse optical flow (Lucas-Kanade Optical Flow algorithm) in this paper.

The velocity of each corner is the displacement of the corner in two consecutive frames divided by the time elapsed between the two consecutive frames. One pedestrian has 2 or more corner. Each micro state probability is calculated according to the equation (3), as shown in Fig1(d) in which each grid represents one micro state and the probability.

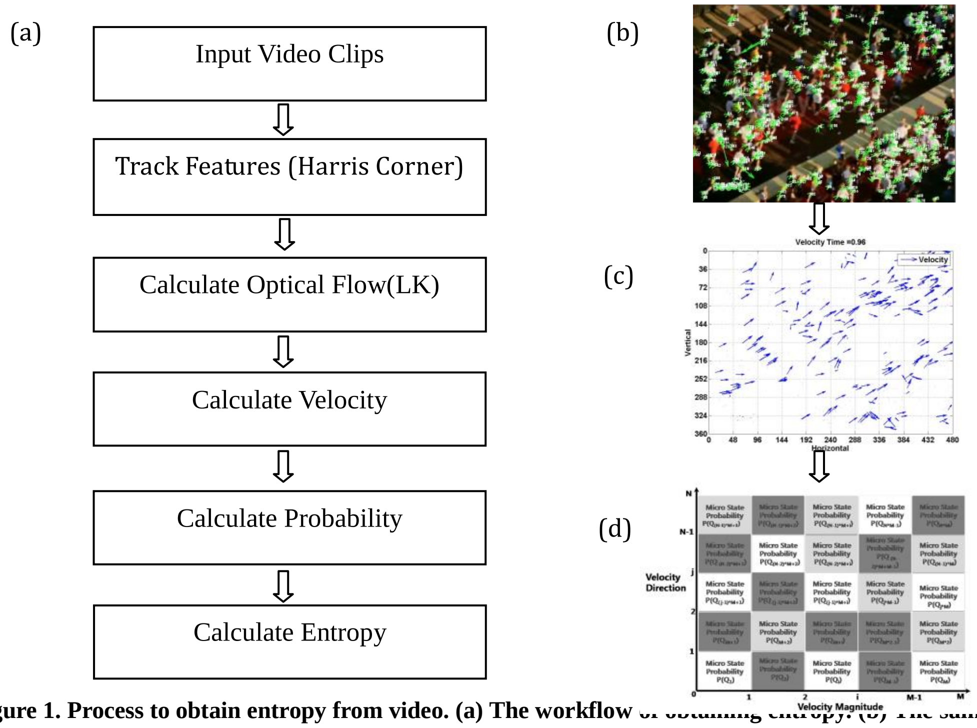

Figure 1. Process to obtain entropy from video. (a) The workflow of obtaining entropy; (b) The sample Harris corners in video; (c) The sample of velocity field; (d) The probability of each micro state.

According to equation (2), the entropy is obtained by the calculation of statistical average of each micro state probability (Fig 1(d))

EXPERIMENTS AND DISCUSSION

To validate the performance of the proposed method, three experiments were conducted. The first two using videos to extract individuals speed, and crowd entropy were calculated in the disordered and ordered statues. In the third experiment, a simulation was performed to present the crowd mutation using a simplified social force model.

Disordered status detection

A video clip was analyzed to obtain the crowd entropy. There are about 120 pedestrians walking randomly in the around 68 square meters space in a famous tourist destination. This is the typical scenario of pedestrians sightseeing and walking around.

The pedestrians were tracked for 21.6 seconds. The frame per second is 25 and 540 frames are analyzed. Figure 2(a) shows the sample frame of the disordered crowd motion. Each individual has different velocity direction and magnitude. Figure 2(b) shows the Harris corners in one sample frame. There are 499 corners in this frame to represent the 120 pedestrians' velocity features.

(a) (b)

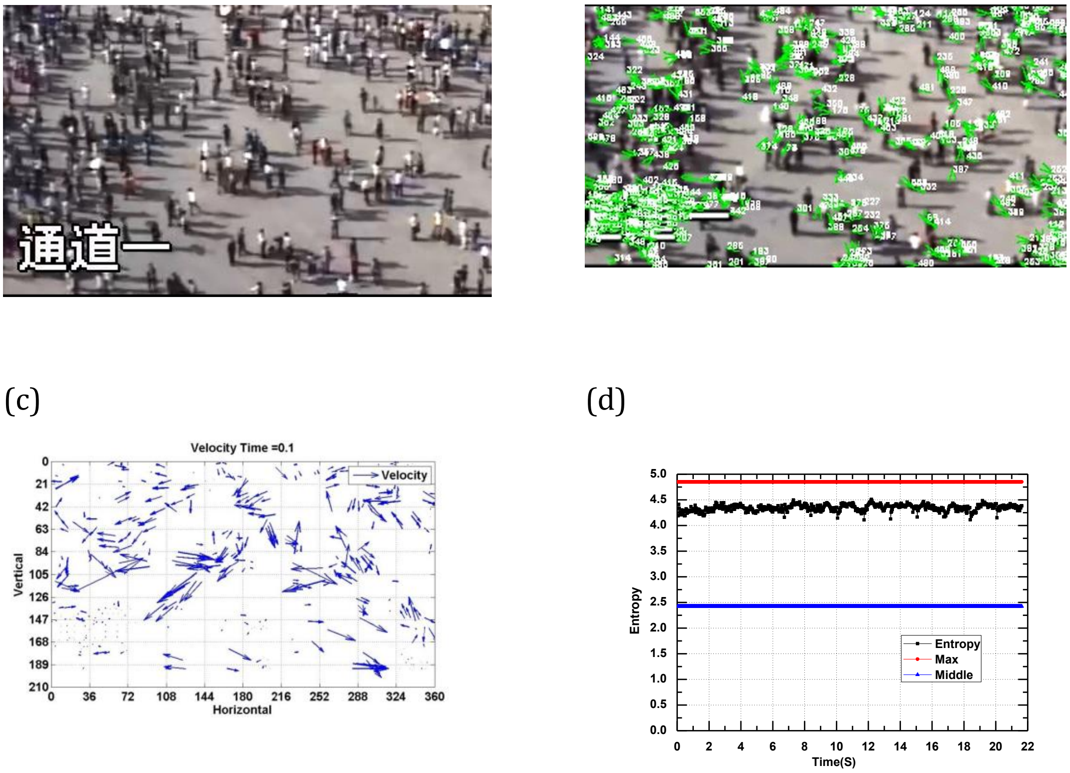

Figure 2. Video experiment results with 120 pedestrians walking randomly in the around 68 square meters space. (a). sample frame of detected pedestrians random.(b).Harris Corners in one sample frame.(c)Velocity field presentation of dynamics features in the x, y plane. Arrow length represents pedestrian speed. (d). The entropy calculated based on 540 video frames.

In this experiment, velocity magnitude varied from 0-1.3 m/s, and divided into 8 partitions. The directions varied from 0-360 degrees, and divided into 16 partitions. Based on equation (4), the theoretical maximum entropy equals to 4.85.

Fig. 2(c) shows the magnitudes and directions of the individual velocities are different in the disordered crowd status. Fig. 2(d) shows the crowd macro status entropy is high and fluctuates very little from 0-21.6 seconds. It is close to the red line (theoretical maximum entropy) and is above the blue line (half of the theoretical maximum entropy). The blue line indicates the threshold distinguish between the disorder and ordered statuses. High entropy represents the highly disordered state of crowd motion, which fits with the expectation. The experimental results is lower than the theoretical maximum entropy, which means the real crowd state is not in the most disordered status, thus called the equilibrium status by Prigogine (Prigogine and Nicolis, 1977).

Ordered status detection

A video available from the Web Dataset (Dataset) is analyzed. The total partition number of the velocity magnitude and direction are the same as the previous experiment. The maximum value of entropy is 4.85.

Pedestrians are running towards the same direction which shows the fully ordered motion status. One sample frame is shown in Figure 3(a). Figure 3(b) shows the Harris Corners in one sample frame. There are 500 corners in this frame to represent the pedestrians' velocity features.

The corresponded velocity field is extracted and calculated in Figure3(c). It shows that the agents have the almost same velocity direction and magnitude.

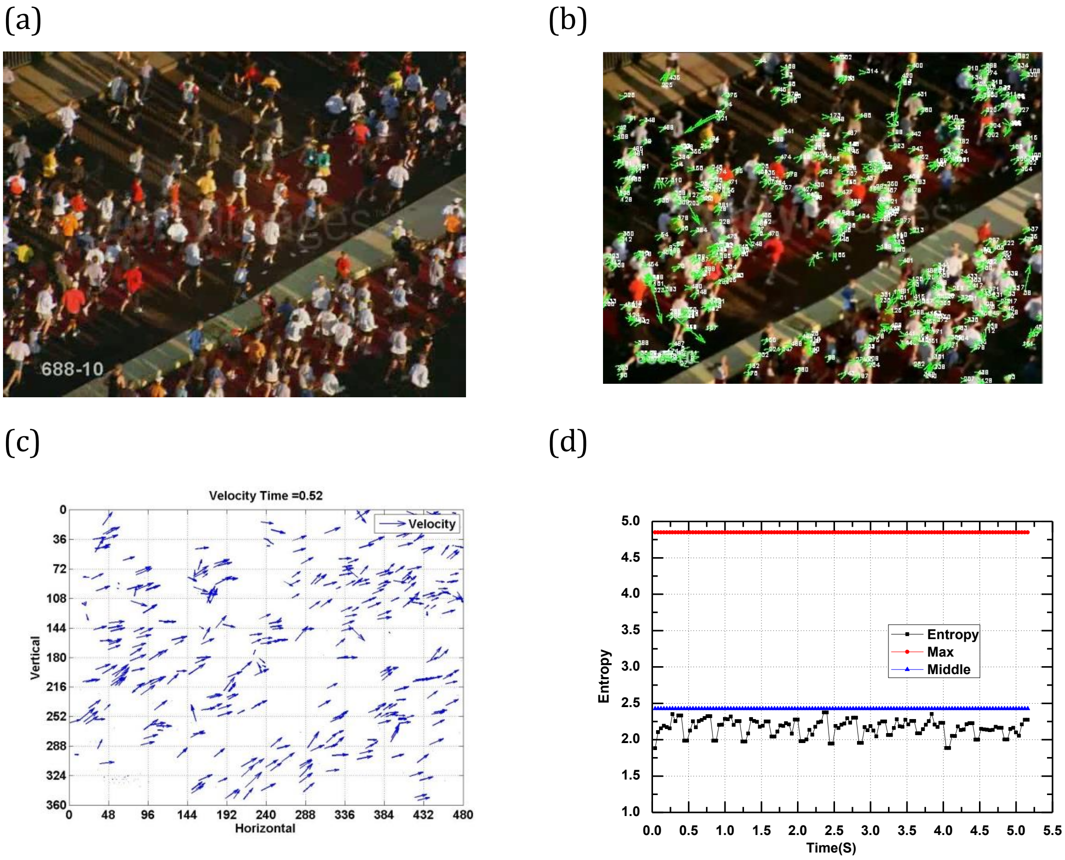

Figure. 3: Example and results from Web Dataset : (a) Sample frame of detected fully ordered crowd status; (b). Harris corners of one sample frame(c).Velocity field of the crowd on 0.52 second since calculation; (d) crowd status entropy versus time in 5.5 seconds.

The total crowd status entropy is shown in Figure3 (d). It is under the blue line and far away from the maximum entropy (the red line) which shows the crowd motion is ordered. The low value of entropy (near the threshold line) represents the ordered state of crowd motion.

In this experiment, the lower value entropy represents the ordered state of crowd motion, which fits with the expectation.

Crowd mutation detection

In this experiment, a crowd mutation is simulated using the simplified social force model (Helbing and P.M, 1995). The scenario includes 200 pedestrians walking on a playground, which size is 10m×10m (length × width).

Here the social force model was amended based on the assumption that agent-agent interactions are governed by the exponential repelling force. The attractive force between the pedestrians is assumed zero, since each agent wants to avoid collision.

First, N=200 pedestrians walking randomly on a ground, with randomly allocated objects, thus presents a disordered status; then a terrorist attack suddenly occurred after two seconds, leading pedestrians run toward the only exit, thus presents an ordered crowd motion. The crowd motion system is considered as an open system. The terrorist attack was realized by inducting an external artificial force(each pedestrian desired object was set to [100 100], thus the attractive is stronger).The mean velocity of agents is 1m/s and the standard deviation is 0.26 to simulate the normal walk of pedestrians. When the pedestrian approaches the boundary, he will walk

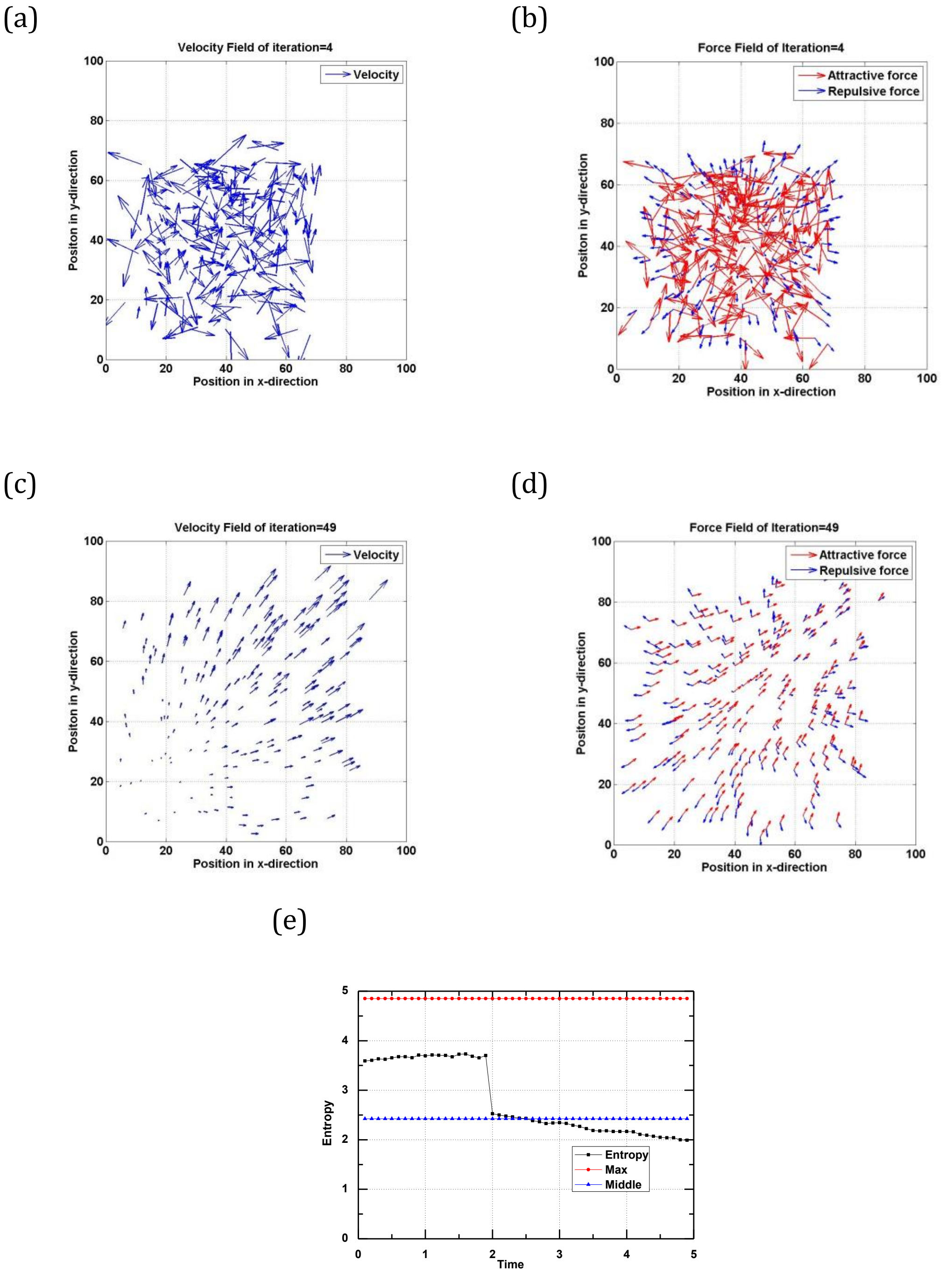

Figure 4.The Social Force Simulation and results of N=200 pedestrians walking on a playground, which size is 10m×10m (length×width).(a) Velocity field after 4th iteration in the x, y plane..(b)Force field after the 4th iteration in the x, y plane. Red arrows represent attractive force while blue arrows represent repulsive force. (c) Velocity field after the 20th iteration. (d) Force field after the 49th iteration. (e). crowd status entropy versus time in 5 seconds.

backward 1 meter in the next second. The iteration frequency is 0.1 second, and the total simulation period lasts for 10 seconds.

Figure 4(a) shows the velocity field after the 4th iteration. Pedestrians move randomly to their respective desired object. The disorder status is presented as assumed. Figure 4(b) shows the attractive force field to the individual targets and the repulsive force field to each other after the 4th iteration. The force field is in chaos since the agents walk randomly.

Figure 4(c) shows the velocity field after the 49th iteration. The pedestrians were approaching the same object with different velocities magnitudes. Figure 4(d) shows the force field after the 49th iteration. The attractive forces show almost the same direction, thus indicate the crowd is in the ordered status

The total crowd status entropy (Figure4 (e)) is above the middle blue line from the 1st to the 19th iteration. Then a sharp drop occurs on the 20th iteration, which reflects the phase transition from the disordered to the fully ordered status. The entropy goes below the blue line on 22th iteration, indicating the crowd system is more ordered. In this experiment, the entropy shows a sudden change when crowd mutation occurred, which verified the assumption that crowd behavior state change leads to the crowd behavior entropy change. It is concluded that the entropy can represent the crowd behavior macro state.

According to the entropy change in Figure 4, an early warning alarm can be created. If a linear regression model is fitted every 0.5 seconds, then the slope of the regression line can reflect the average entropy rate within 0.5 seconds. The severity of an alarm could be measured as the angle of the regression line divided by 90. Then a line to depict the alarm level can be drawn by computing the angle of the regression line divided by 90. If a threshold is set in the line, then alarm time and level can be computed.

The detection of the crowd motion status is useful in the crowded areas. The sudden entropy change might indicate the initial stage of a mass event. For example, the sudden entropy decrease presents the crowd status change from the ordered to the ordered crowd behavior, which might be caused by religion ceremony, or illegal public gathering. On the contrary, the sudden entropy increment presents the crowd status change from the ordered to the disordered crowd behavior, which might due to a sudden fire, explosion, car accident or other artificial force involved events. By recognizing the entropy sudden transition, the precaution methods should be arranged to prevent the public accidents.

CONCLUSION AND OUTLOOK

In this study, the crowd behavior entropy model based on Shannon entropy model was constructed as a measure to detect crowd security status, by using the individual velocity and its probability to represent the crowd micro state. Three experiments were conducted to validate the crowd behavior entropy model. In disordered and ordered status analyses, crowd motions were presented by extracting the individual velocities from the video frames. Crowd status entropies were calculated, and compared with theoretical maximum entropy. The line presents the value of the half of the theoretical maximum entropy is the threshold line to distinguish between the disorder and ordered statuses. Results show that in the disordered state, the crowd status entropy is much higher than the threshold line, and close to the theoretical maximum entropy line. In the ordered state, the crowd status entropy is much lower than the threshold line.

In the simulation experiment, a scenario was assumed, in which a crowd behavior sudden change was included. The sharp crowd status entropy drop was presented and analyzed. The results verified the case that the detection of entropy sudden change is a way to recognize the crowd behavior sudden change. The crowd mutation from disordered motion to ordered motion which were possibly caused by religion ceremony, or illegal public gathering. The crowd mutation from ordered motion to disordered motion might be caused by explosion, terror attack or other accidents. This paper provides an entropy model to predict crowd mutation. Thus precautions could be made to prevent the mass emergency and disaster on the initial stage.

This paper is the first attempt to construct an entropy model to describe the crowd macro state. The construction of crowd micro states in this paper make it possible to set up an crowd entropy model.

The entropy rate (Gray, 2012) describing the entropy value per time unit will show more details on the crowd motion features in our future research. Although it is verified in the above experiments that crowd mutation leads to entropy mutation, the relationship between the severe degree of the entropy mutation and crowd mutation is not clear. It will be the next research to verify whether it is feasible to confirm early warning level by using entropy rate.

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REFERENCES

1. A, Borislav., B.Ommer. (2011) Video Parsing for Abnormality Detection, IEEE International Conference on Computer Vision, 2415-2422
2. Bouguet, J.-Y. (2001) Pyramidal implementation of the affine lucaskanade feature tracker description of the algorithm, Intel Corporation.
3. Cao, T, Wu, X, Guo, J, Yu, S, Xu, Y. (2009) Abnormal crowd motion analysis, IEEE International Conference on Robotics and Biomimetics (ROBIO),, 1709-1714
4. Dataset, Web. (2014) Abnormal/Normal crowds,http://www.cs.ucf.edu/~ramin/?page_id=24#VI._Downloads, 2014.
5. E, Shannon C. (1948) A mathematical theory of communication Bell System Technical Journal, 27,3, 379-423,623-656.
6. Gray, Robert M. (2012) Entropy and Information Theory,Second Edition, Second ed., China Science Press, Beijing.
7. Harris, C, Stephens, M. (1988) A combined corner and edge detector, Alvey vision conference.Manchester, UK
8. Helbing, Dirk, Johansson, Anders. (2007) The Dynamics of Crowd Disasters: An Empirical Study, Physical review E, 75,4, 046109.
9. Helbing, Dirk, P.M. (1995) Social force model for pedestrian dynamics, Physical review E, 51,5, 4282-4286.
10. J, Shi., Tomasi, C. (1994) Good features to track, IEEE Computer Society Conference on Computer Vision and Pattern Recognition,
11. Krausz, Barbara, Bauckhage, Christian. (2012) Loveparade 2010: Automatic video analysis of a crowd disaster, Computer Vision and Image Understanding, 116,3, 307-319.
12. Louis Kratz, Ko Nishino. (2009) Anomaly Detection in Extremely Crowded Scenes Using Spatio-Temporal Motion Pattern Models, IEEE Conference of Computer Vision and Pattern Recognition, 1446-1453
13. Ma, J, Song, W G, Lo, S M, Fang, Z M. (2013) New insights into turbulent pedestrian movement pattern in crowd-quakes, Journal of Statistical Mechanics: Theory and Experiment, 02028.
14. Pathan, Saira Saleem, Al-Hamadi, Ayoub, Michaelis, Bernd, Incorporating Social Entropy for Crowd Behavior Detection Using SVM, in: (2010) International Conference on Intelligent Structure and Vibration Control (ISVC) pp. 153-162.
15. Prigogine, Ilya, Nicolis, G. (1977) Self-Organization in Non-Equilibrium Systems, Wiley.
16. Ramin Mehran, Alexis Oyama, Mubarak Shah. (2009) Abnormal Crowd Behavior Detection using Social Force Model, Computer Vision and Pattern Recognition 935-942.
17. Stavens, D. (2007) The OpenCV library: computing optical flow, Stanford Artificial Intelligence Lab.
18. Vicsek, T. (2008) Universal Patterns of Collective Motion from Minimal Models of Flocking, Second IEEE International Conference on Self-Adaptive and Self-Organizing Systems, 3-11.Venice, Italy
19. Vijay Mahadevan, Weixin Li, Viral Bhalodia,Nuno Vasconcelos. (2010) Anomaly Detection in Crowded Scenes,
20. XuxinGua, Cui, Jinrong, Zhu, Qi. (2014) Abnormal crowd behavior detection by using the particle entropy, Optik, 3428–3433.
21. Zhang, X.L., Weng, W.G., Yuan, H.Y., ., J.G. Chen. (2013) Empirical study of a unidirectional dense crowd during a real mass event, Physica A: Statistical Mechanics and its Applications, 392, 12, 2781-2791.