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ORIGINAL ARTICLE

Crowd Behavior Monitoring using Self-adaptive Social Force Model

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ABSTRACT – Crowd can be defined as a large number of people gathered closely together. The larger size of crowd results number of behavior either in group or individually. To prevent or minimize the effects of the abnormal behavior, it has to be monitored continuously. Crowd behavior monitoring is an important task in public places to ensure public safety and avoid any unwanted incidents. It has become a popular research among computer vision communities nowadays due to its needs by the authorities. The current method used is Social Force Model (SFM), which can describe the behavior of a crowd based on the interaction forces between individuals. However, some limitations in the previous works caused by its parameters make it fail to correctly classify the crowd behavior into normal or abnormal. Hence, some modification has been introduced to SFM theory in order to provide significant interaction force; which absolutely portrayed the behavior of the crowd. This work aims to develop a crowd behavior monitoring system using Self-Adaptive SFM. This algorithm is jointly used with Horn-Schunck optical flow as a motion detector for the input video. Instead of using any segmentation methods, the motion of particles in each frame is captured by particle advection method. This is done by advected the particles using the underlying flow vectors of each particle. The obtained new locations for all the particles are necessary in estimating the interaction force of each particle. The combination of psychological and physical parameters in Self-Adaptive SFM makes it more realistic and mimicked the dynamic motion of people in a crowd. The estimated interaction forces of each particle represent the behavior of the crowd, whether it is normal or abnormal. The experimental evaluations on challenging datasets shows that the proposed method achieves the better detection result and outperforms the other methods, optical flow and SFM; with the average accuracy of about 94%.

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Introduction

Public security has become the most significant issue in public places such as light rail transit (LRT) stations, market, malls and banks. The increase of crowd occurrence in these public places may increase the probability of criminal cases occurred and unnecessary injuries or fatalities [1, 2]. Over few years, video surveillance systems [3-8] has been introduced and widely used in the public places. It is said to be useful to human observer, whereby this systems can provide real-time data of crowds in the region of interests to them. However, one common drawback among these systems is their inability to handle high density crowds [9]. The typical large area surveillance system is characterized by a large network of (closed-circuit television) CCTV cameras, which all connected to a control room, where a human operator performs the complicated task to monitor all of them. It is nearly impossible for the human observers to interpret all the data manually for abnormal and emergency events in the high density crowds. Hence, the need for automated system is become crucial. So, this work will focus in automated surveillance system.

The main component of automated surveillance system is crowd analysis. The crowd analysis can be categorized into three groups, which are abnormal detection [10-18], behavior recognition [19-21] and motion pattern segmentation [22-24]. This works underlie the abnormal detection part in the crowd scene.

Related Work

The main contribution of this work is a visual surveillance system based on modified SFM method; which is automated and self-adaptive. The term self-adaptive in this work differentiate between this proposed model with other previous models of SFM [11, 15, 25-28]. SFM is first introduced by Helbing et al. [29, 30] in 1995. It is a model of pedestrian dynamics which can describe the behavior of the individual pedestrians by a simple social force model. In this model, two assumptions have been made which may affect the motion of the pedestrian. (i) This model assumes that each pedestrian wants to reach destination as comfortable as possible. Therefore, the shortest path normally will be taken with a desired speed to the desired destination. (ii) This model also assumes that each individual has a force that motivated to move to a desired direction; called interaction force. It is consists of two other forces; attractive and repulsive force. Both forces are based on psychological tendency to keep a distance between individuals and to avoid obstacles like walls, buildings and others. The forces and velocities in SFM are visualized in Figure 1.

SFM can be split into two types; the original SFM by Helbing et al. [29] and the modified version of SFM by Mehran et al. [11]. There are many works explored the original SFM [30-43] but this model is limited to simulating and modelling the behavior of pedestrians and robots. Due to this limitation, this works lie behind the modified version of SFM, which is more suitable to describe the behavior of a crowd. It is simpler than the original SFM which have a lot of parameters need to take into account when modelling the behavior of a crowd.

The modified version of SFM was introduced in computer vision field by Mehran et al. [11] in 2009. The developed SFM-based method is to detect and localize the abnormal behavior in a crowd. In this works, particle advection is implemented; which is an earlier framework introduced by Ali et al. [45] to compute particle flows and capture the trajectories of the particles. The interaction forces are estimated using SFM. The normal behavior of the crowd is model by randomly selects the spatio-temporal volume of the force flows and trained using Latent Dirichlet Allocation (LDA). The localization of the anomaly is based on the high magnitude of interaction force, which portrayed the abnormal behavior in the crowd.

Few years later, SFM method is hybrid with the optimization method. It was invented by Raghavendra et al. [15, 27] in 2011. They introduced a particle swarm optimization (PSO) in the particle advection in order to estimate the direction of the particles moved. This method is said able to optimize the interaction force estimated by SFM. The PSO acts to drift the population of the particles towards the region of the main image motion using the PSO fitness function. For the global anomaly detection, fixed thresholding method is used to classify a crowd scene as normal or not. However, the threshold method used is too restrictive and scene dependent. So, it is not well discovered with the variations and changes.

Addressing the limitations in Raghavendra et al. [15, 27] , Zhu et al. [46] proposed a new approach for estimating the interaction force in the SFM-based framework. In their approach, the properties of individuals such as distance apart, motion consistence and angle-of-view were fully utilized in interaction force estimation. They also implemented particle advection, but in the different way to Ali et al. [45] and Mehran et al. [11]. They used the algorithm in [47] as

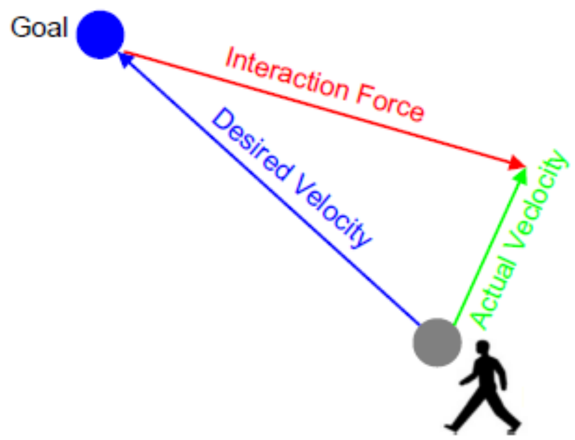


Figure 1. Visualization of force and velocities in SFM [44].

particle advection. All the properties mentioned above were jointly considered, assuming that individuals with consistent motion (as a particle group); ones out of the angle-of-view have no influence on each other and the apart ones have weak influence. The particle groups were clustered by spectral clustering; using the combined discriminative gait feature, spatial and motion feature. The extracted bag-of-words force flow then being classified using Sparse Topical Coding (STC).

Instead of using properties of surrounding individuals, Yanhao et al. [26] did explored the richness of the estimated interaction force. They novel a social attribute-aware force model (SAFM) for abnormal crowd events detection, which incorporate social characteristics of crowd behaviors. Two attributes introduced in their works; social disorder and congestion attributes. The crowd interaction models were constructed on the basis of SFM by using online fusion strategy. The main contributions of their works are: (i) propose a fast scene scale estimation scheme which captures the scene perspective to better infer crowd characteristics. The scale attribute and density properties of the crowd were extracted by partitioning the foreground movements from the background. (ii) Introduced social disorder and congestion attributes constructed by quantitative measurement of the motion features. (iii) Emphasized the social semantic influence on the crowd interaction behaviors by using the proposed SAFM. Based on the results, the proposed model provide good performances and robust to the various content and changes. However, the online fusion method is time consumed because the algorithm needs to combine a few set of attributes; interaction force, disorder and congestion attributes on the basis of SFM.

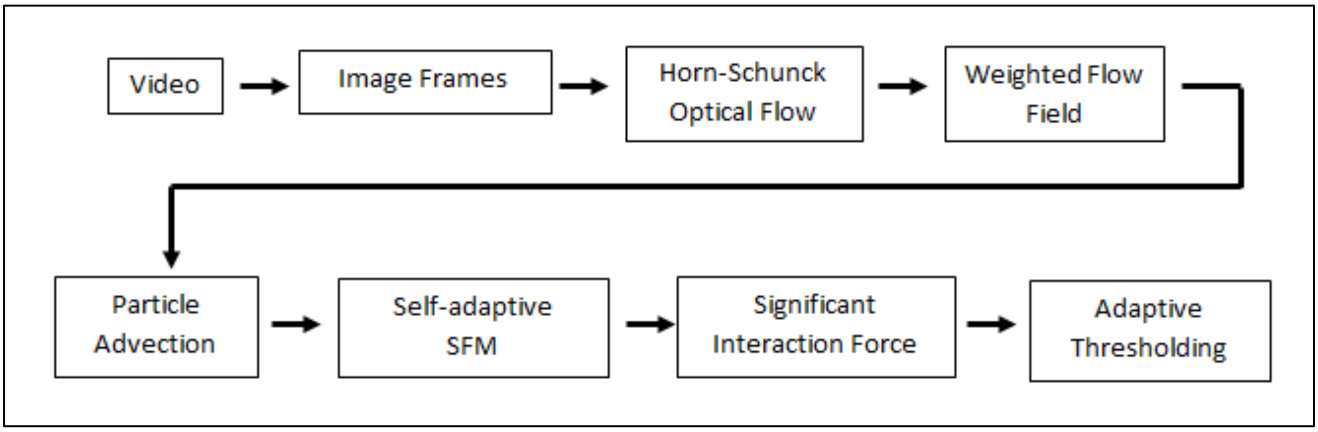


Figure 2. Proposed framework

Methods

This section describes the methods used in this work, as illustrated in Figure 2. The works begin with the extracting the video into image frames. Next, all the frames will go through Horn-Schunck optical flow to get the flow vector for each frame, following by particle advection using linear interpolation, estimation of interaction forces and computing the significant interaction force using self-adaptive SFM. The decision is made based on adaptive thresholding method. The detail descriptions for each method are described in the subsections.

Motion detection using Horn-Schunck optical flow

Horn-Schunck optical flow [48] is used in this work as a motion detector for the input video since it is simple but offers robustness when dealing with high density flow field. Compared to other optical flow methods [49-51], Horn-Schunck optical flow is the most suitable used in this work because it examined each pixel movement in the image frame. The input video is extracted into image frames and the optical flow is implemented to the sequence of image frames.

In optical flow, the motion in the image frame is obtained from the pixel movements. It is the change of brightness intensity of the pixel between two consecutive frames and the movement of the pixel produces a flow field, as well as the flow vector, u and v. Figure 3(a) illustrates one of the image frames and Figure 3(b) represents the corresponding flow field for the left side image. The arrow represents the moving man in the image frame and the dots symbolized the moving pixels with too small difference or static and can be neglected in further process.

In order to get a smooth flow field, Gaussian filter is used to eliminate the noise in the scattered flow field. The filtered flow field will then be used in particle advection scheme using linear interpolation method.

Motion detection based on linear interpolation

Particle advection is a process where the particles are moved along or advected by a flow. There are 99 particles initialized on identical grids on the image frame. Then, they were advected by the flow vector underlying the particles. This method is similar to Ali et al. [45] and Mehran et al. [11], except the way to compute the velocity of the particles. Instead of using optimization as [15, 27] in estimating the new location of the particles, linear interpolation is used to compute the current location of the particles. The equations are shown as follows:

$$X_{new} = X_{previous} + u_{current} \tag{1}$$

$$Y_{new} = Y_{previous} + v_{current} \tag{2}$$

Using the linear interpolation method, the current coordinates of all particles are being updated frame by frame and the velocity for each particle can be computed. Different with others [11, 14, 16, 17, 27, 28], the velocity is calculated using the motion equation in physics instead of using 4th order Runge-Kutta algorithm; which provides unpredictable trajectories and unstructured flow. The equation used is:

$$Velocity = \sqrt{u^2} + \sqrt{v^2} \tag{3}$$

The pseudo code for the particle advection scheme is as follows:

Algorithm 1 : Particle Advection
Input: Optical flow computed for the whole set of video frames
Initialization: Initialize particle position $\{x_i, y_i\}_{i=1}^{k}$ *k* is the number of particles.
read video (Data 1…Data *n*) extract video to image frames compute optical flow $uv_{i=1}^{k}$ compute new particles' coordinates new location (x_{new}, y_{new}) = previous location ($x_{previous}$, $y_{previous}$) + optical flow (*uv*) compute velocity each particle

The particle advection scheme is initiated with the data acquisition and the video clip is extracted into image frames. Then, the optical flow for each frame is computed and produced vector u and v. These vectors are used to estimate the trajectories of the moving particles in the image frame. Using the current location of the particles, the velocity of each particle is computed using Equation 3.

Figure 4(a) illustrates the initialized particles of the image frame and the red circle denotes some of the moving particles that will be highlighted. Figure 4(b) portrays the trajectories of the highlighted particles, which has moved to the new locations.

Once the current and previous locations of particles obtained, the interaction forces can be estimated using the self-adaptive SFM.

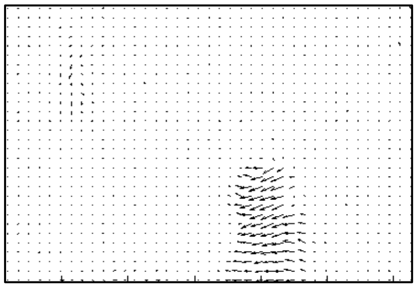
Estimation of interaction forces

Using the previous and current locations of particles from the previous subsection, the interaction force is estimated using self-adaptive SFM. Following Mehran et al. [11], each of individual, i with mass of m_i changes his/her velocity, v_i as:

$$m_i \frac{dv_i}{dt} = F_a = F_p + F_{\text{int}} \tag{4}$$

The environments and individual constraints results the actual force F_a. This actual force consists of two forces; personal desire force F_p and interaction force F_{int}. Generally, people in crowd strive for certain goals and destinations in the environment. Therefore, it is reasonable to consider that individual have a desired direction and velocity v_i^p. However, the individual movement is limited due to the crowd and the actual motion of individual will be diverge from the desired velocity. Individual tend to approach his/her desired velocity based on the personal desire force:

(a)



(b)

Figure 3. (a) A sample of frame of a scene, (b) The corresponding flow field.

$$F_p = v_i^p - v_i \tag{5}$$

Adding psychological influence in the mathematical model, where individuals keep a distance among them and avoid hitting any obstacles, the interaction force F_{int} becomes:

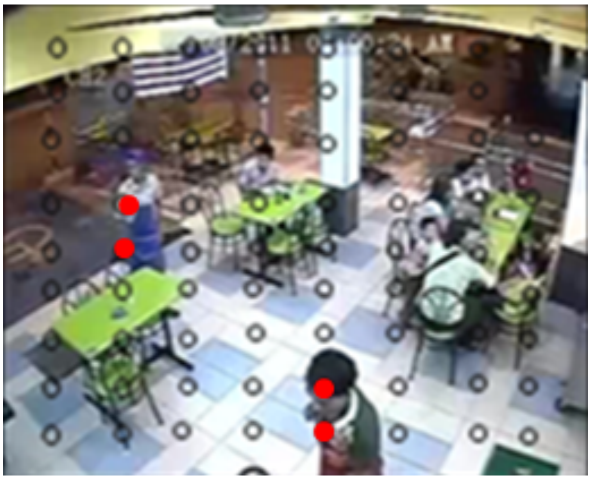
$$F_{\text{int}} = F_{ped} + F_w \tag{6}$$

Based on the equation, the interaction force consists of attraction and repulsive force F_{ped} and an environment force F_w. When considering the effect of panic, where herding behaviors happen, the personal desired velocity v_i^p is replaced with:

$$v_i^q = (1 - p_i)v_i^p + \langle v_i^c \rangle \tag{7}$$

where p_i is the panic weight parameter and $<v_i^c>$ is the average velocity of the individuals' neighbours. Generalized SFM is summarized as:

$$m\frac{dv_i}{dt} = F_a = \frac{1}{\tau}(v_i^q - v_i) - F_{\text{int}} \tag{8}$$



(a)

(b)

Figure 4. (a) The initialized particles, (b) The trajectories of the moving particles.

To jointly used SFM with optical flow, low level attributes from optical flow is adapted with the SFM algorithm. The actual velocity v_i in Equation 8 becomes:

$$v_i = O_{ave}(x_i, y_i) \tag{9}$$

where $O_{ave}(x_i, y_i)$ is the spatio-temporal average of optical flow for the particle i at coordinate (x_i, y_i).

The desired velocity v_i^q becomes:

$$v_i^q = (1 - p_i)O(x_i, y_i) + p_i O_{ave}(x_i, y_i) \tag{10}$$

where $O(x_i, y_i)$ is the optical flow of particle i with coordinate (x_i, y_i).

The interaction forces for each particle are computed using Equation 8, by substituting v_i and v_i^q in that equation. Figure 5 illustrated the interaction force computed using SFM. The interaction forces are depicted by the green arrows on the image frame.

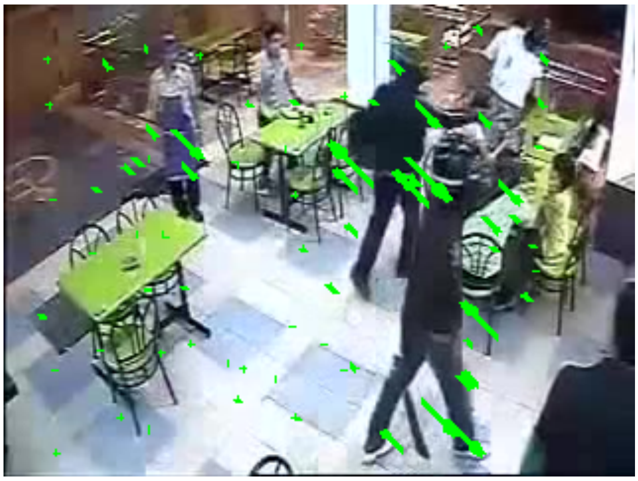


Figure 5. Interaction forces computed using SFM.

Significant interaction force using self-adaptive SFM

The significant interaction is important in classifying the crowd into normal or abnormal state. The interaction force computed in the previous subsection portrayed the behavior of a crowd. However, when the desired velocity is similar to actual velocity, the interaction force failed to prove this. So, self-adaptive SFM is proposed in order to get the significant interaction force that is truly represents the behavior of the crowd. The interaction force is weighted with Fisher Score (FS) so that the noisy interaction force is filtered to get the significance ones. It has been modified to be adapted with the computed interaction force using SFM as follows:

$$\overline{F_{\text{int}}} = \frac{F_{\text{int}1} + F_{\text{int}2} + F_{\text{int}3} \ldots + F_{\text{int}n}}{n} = \frac{\sum_{i=1}^{n} F_{\text{int}_i}}{n} \tag{11}$$

where F_{int_i} is the interaction force for frame i and n is the number of frames.

The variance of interaction force $v_{F_{\text{int}}}$ is presented as:

$$v_{F_{\text{int}}} = \frac{\sum_{i=1}^{n} (F_{\text{int}_i} - \overline{F_{\text{int}}})^2}{n} \tag{12}$$

where F_{int_i} is the interaction force for frame i and n is the number of frames.

The significant interaction force F_{sig} is denotes as:

$$F_{sig} = \frac{(\overline{F_{\text{int}1}} - \overline{F_{\text{int}2}})^2}{v_1 + v_2} \tag{13}$$

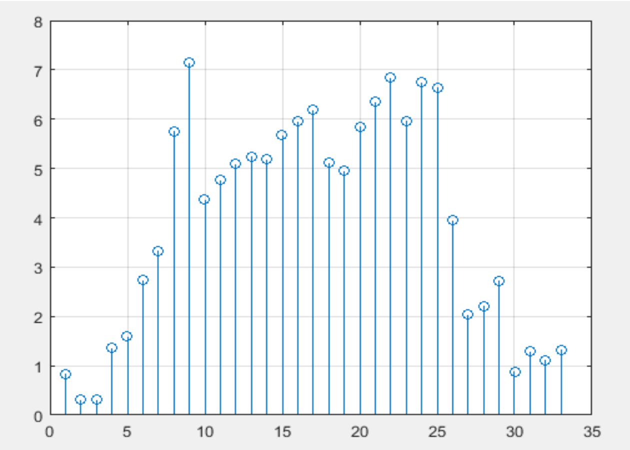


Figure 6. Significant interaction forces of each frame.

The pseudo code for this modified algorithm is shown as follows:

Algorithm 2 : Proposed algorithm based on SFM
Input: Optical flow and average optical flow computed for the whole set of video frames O, O_{avg}
Initialization: Initialize particle velocity and position $\{v_i\}_{i=1}^{k}, \{x_i\}_{i=1}^{k}$ k is the number of particles.
compute optical flow $uv_{i=1}^{k}$
compute actual velocity $O_{avg\,i=1}^{\;k}$ using Eq. (3.20)
compute desired velocity v_i^q using Eq. (3.21)
compute interaction force F_{int} using Eq. (3.19)
find unique class of F_{int} (two classes)
find indexes for both classes
compute mean and variance of each class
compute significant interaction force using Eq. (3.25)

Figure 6 illustrates the significant interaction forces for each frame calculated using Algorithm 2. The stem plot can be split into three states, Frame 1 to Frame 7, Frame 8 to Frame 25 and Frame 26 to Frame 33. The first state represents the normal part of the scene due to the small magnitude of significant interaction force. The abnormal state begins in Frame 8 to Frame 25 and become normal in Frame 26 to Frame 33.

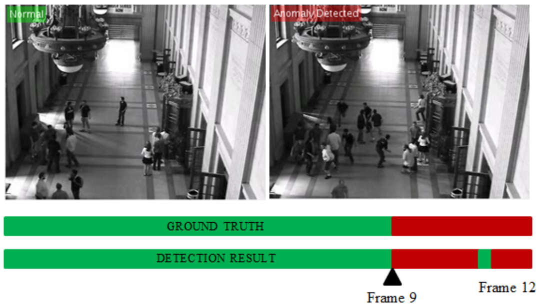
Figure 7. (a) and (b) normal frames. (c) and (d) abnormal frames.

Figure 8. Qualitative results of detection.

Decision

Usually in classification or decision stage for crowd monitoring, supervised learning methods is implemented to train the behavior of the model before testing it [11, 15-17, 52]. For instance, many of previous works trained the normal patterns of a video and tested the video, which contained both normal and abnormal patterns. So, if the testing pattern did not same with the normal ones (training patterns), the scene will be classified as abnormal. However, this method is not suitable with the crime video since it is difficult to get the normal ones. Instead of using any learning methods, adaptive thresholding is implemented to get a limit value according to the crowd scene. The adaptive term refers to its function to adapt with any crowd videos and provides the threshold value for each scene.

Figure 7 (a)-(d) are the detection results using the proposed algorithm and these qualitative results are also presented as shown in Figure 8.



Method	Area under curve (AUC)
Optical Flow	0.3758
SFM	0.7478
Modified SFM	0.9502

Figure 9. One of the video in UMN dataset.

Experimental evaluations

The proposed algorithm is validated with others ten videos to investigate its performance on other datasets. The other datasets include UMN, PETS 2009 and Malaysia Crime dataset as shown in Figure 9, 11 and 13. The proposed method is compared with the optical flow and SFM.

Figure 10 portrays the ROC curve on UMN dataset using the proposed algorithm. The results show that the proposed algorithm outperforms the others with the area under curve (AUC) 0.9502.

The ROC curve plot for PETS2009 dataset is illustrated in Figure 12. The AUC also the highest, which is 0.8765 followed by 0.8528 using SFM and 0.7050 using optical flow. The AUC result that is obtained is lower compared to the other datasets due to slow transition of the movements in the video dataset.

Figure 14 shows the ROC curve on Malaysia Crime dataset. The detection result for proposed algorithm is 0.9200; outperforms the SFM and optical flow method.

Summary

Based on the qualitative and quantitative results, it can be concluded that proposed algorithm leading the detection compared with SFM and optical flow. It is works well on challenging dataset; Malaysia Crime dataset since it can adapt with the variations of the motion characteristics and illumination changes of the foreground and background of the scene. From the analysis, the proposed algorithm works accurately with the datasets comprises of rapid movements data.

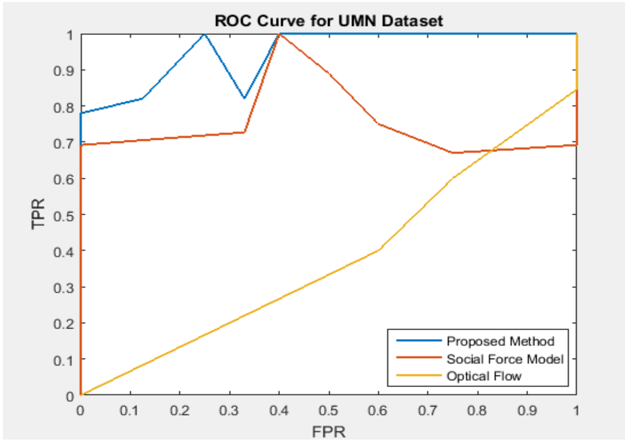
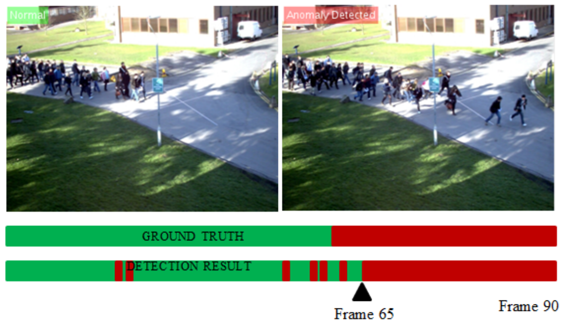


Figure 10. ROC curve on UMN dataset.



Method	Area under curve (AUC)
Optical Flow	0.7050
SFM	0.8528
Modified SFM	0.8765

Figure 11. One of the video in PETS2009 dataset.

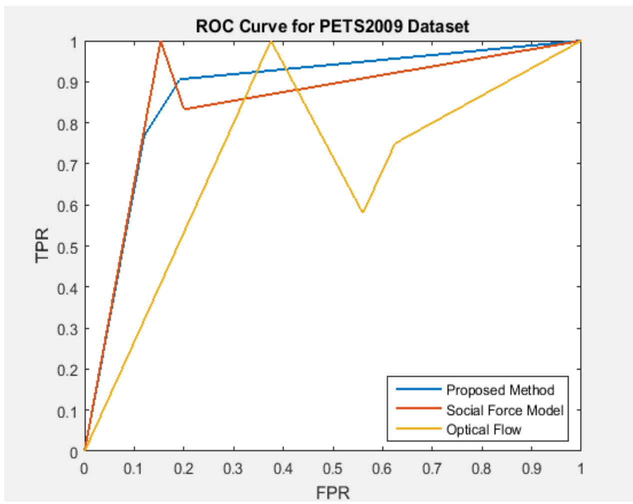


Figure 12. ROC curve on PETS2009 dataset.

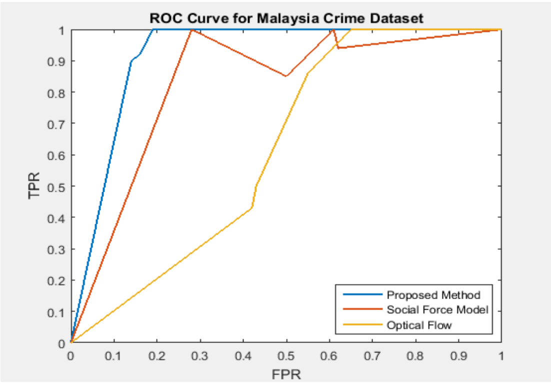
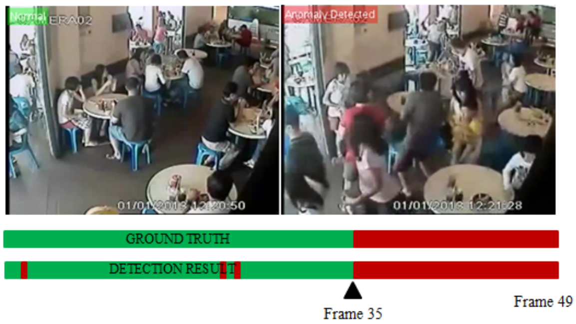


Figure 13. One of the video in Malaysia Crime dataset.



Method	Area under curve (AUC)
Optical Flow	0.6196
SFM	0.8236
Modified SFM	0.9200

Figure 14. ROC curve on Malaysia Crime dataset.

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References

[1] S.Yaseen, A.Al-Habaibeh, D.Su, and F.Otham, “Real-time crowd density mapping using a novel sensory fusion model of infrared and visual systems,” *Safety Science*, vol. 57, August, pp. 313-325, 2013.

[2] Coppola, D. P., Introduction to International Disaster Management, Elsevier, 2011.

[3] Ehtesham Hassan and Avinash Kumar Maurya, “Real-time video analysis for retail stores,” In Proc. Sixth International Conference on Graphic and Image Processing, vol. 9443, 2015.

[4] Regazzoni, C. S., Tesei, A., and Murino, V., “A real-time vision system for crowding monitoring,” In Proc. 19th Annual Conference of IEEE Industrial Electronics, pp. 1860-1864, 1993.

[5] Thida M., Yong Y.L., Climent-Pérez P., Eng H.,and Remagnino P., “A literature review on video analytics of crowded scenes,” *Intelligent Multimedia Surveillance: Current Trends and Research*, pp. 17-36, 2013.

[6] Weiming Hu,Tieniu Tan, Liang Wang, and S. Maybank, “A survey on visual surveillance of object motion and behaviors,” *IEEE Transactions on Systems, Man, and Cybernetics, Part C: Applications and Reviews*, vol. 34, no. 3, pp. 334-352, 2004.

[7] Sodemann, A. A., Ross, M. P., and Borghetti, B. J., “A review of anomaly detection in automated surveillance,” *IEEE Transactions on Systems, Man, and Cybernetics, Part C: Applications and Reviews*, vol. 42, no. 6, pp. 1257-1272, 2012.

[8] Davies, A. C., Jia Hong, Y., and Velastin, S. A., “Crowd monitoring using image processing,” *Electronics and Communication Engineering Journal*, vol. 7, no. 1, pp. 37-47, 1995.

[9] Ali, S., “Taming crowded visual scenes,” PhD thesis, University of Central Florida Orlando, Florida, 2008.

[10] Kratz, L. and Nishino, K., “Anomaly detection in extremely crowded scenes using spatio-temporal motion pattern models,” In Proc. IEEE Conference on Computer Vision and Pattern Recognition, pp. 1446-1453, 2009.

[11] Mehran, R., Oyama, A., and Shah, M., “Abnormal crowd behavior detection using social force model,” In Proc. IEEE Conference on Computer Vision and Pattern Recognition, pp. 935-942, 2009.

[12] Shi, Y., Gao, Y., and Wang, R., “Real-time abnormal event detection in complicated scenes,” In Proc. 20th International Conference on Pattern Recognition (ICPR), pp. 3653-3656, 2010.

[13] Xinyi Cui, Qingshan Liu, Mingchen Gao, Dimitris N., and Metaxas, “Abnormal detection using interaction energy potentials,” In Proc. IEEE Conference on Computer Vision and Pattern Recognition (CVPR), pp. 3161-3167, 2011.

[14] Guogang Xiong, Xinyu Wu, Yen-Lun Chen, and Yongsheng Ou., “Abnormal crowd behavior detection based on the energy model,” In Proc. IEEE International Conference on Information and Automation (ICIA), pp. 495-500, 2011.

[15] R. Raghavendra, Alessio Del Bue, Marco Cristani, and Vittorio Murino., “Abnormal crowd behavior detection by social force optimization,” *Human Behavior Understanding*, pp. 134-145, 2011.

[16] Bo Wang, Mao Ye, Xue Li, and Fengjuan Zhao, “Abnormal crowd behavior detection using size-adapted spatio-temporal features,” *International Journal of Control, Automation and Systems*, vol. 9, no. 5, pp. 905-912, 2011.

[17] Hua Yang, Yihua Cao, Shuang Wu, Weiyao Lin, Shibao Zheng, and Zhenghua Yu, “Abnormal crowd behavior detection based on local pressure model,” In Proc. Signal and Information Processing Association Annual Summit and Conference (APSIPA ASC), pp. 1-4, 2012.

[18] Najafabadi, M. M., and M. Rahmati, “Anomaly detection in structured/unstructured crowd scenes,” In Proc. Seventh International Conference on Digital Information Management (ICDIM), pp. 79-83, 2012.

[19] Kok, V. J., Lim, M. K., and Chan, C. S., “Crowd behavior analysis: A review where physics meets biology,” *Neurocomputing*.

[20] Antonakaki, P., Kosmopoulos, D., and Perantonis, S. J., “Detecting abnormal human behaviour using multiple cameras,” *Signal Processing*, vol. 89, no. 9, pp. 1723-1738, 2009.

[21] Bolei, Z., Xiaogang, W., and Xiaoou, T., “Understanding collective crowd behaviors: learning a mixture model of dynamic pedestrian-agents,” In Proc. IEEE Conference on in Computer Vision and Pattern Recognition (CVPR), pp. 2871-2878, 2012.

[22] Benabbas, Y., Ihaddadene, N., and Djeraba, C., "Motion pattern extraction and event detection for automatic visual surveillance," *Journal Image Video Process*, pp. 1-15, 2011.

[23] Mehran, R., Moore, B. E., and Shah, M., "A streakline representation of flow in crowded scenes," In Proc. Computer Vision ECCV, pp. 439-452, 2010.

[24] Benabbas, Y., Ihaddadene, N., and Djeraba, C., "Motion pattern extraction and event detection for automatic visual surveillance," *EURASIP Journal on Image and Video Processing*, vol. 1, pp. 1-15, 2011.

[25] R. Raghavendra, M. Cristani, A. Del Bue, E. Sangineto, and V. Murino, "Anomaly detection in crowded scenes: a novel framework based on swarm optimization and social force modeling," *Modeling, Simulation and Visual Analysis of Crowds*, pp. 383-411, 2013.

[26] Yanhao Zhang, Lei Qin, Rongrong Ji, Hongxun Yao, and Qingming Huang, "Social attribute-aware force model: exploiting richness of interaction for abnormal crowd detection," *IEEE Transactions on Circuits and Systems for Video Technology*, vol. 25, no. 7, pp. 1231-1245, 2015.

[27] R. Raghavendra, Alessio Del Bue, Marco Cristani, Vittorio Murino, "Optimizing interaction force for global anomaly detection in crowded scenes," In Proc. IEEE International Conference on Computer Vision Workshops, pp. 136-143, 2011.

[28] Yanhao Zhang, Lei Qin, Hongxun Yao, and Qingming Huang, "Abnormal crowd behavior detection based on social attribute-aware force model," In Proc. 19th IEEE International Conference on Image Processing (ICIP), pp. 2689-2692, 2012.

[29] Helbing, D., and Molnar, P., "Social force model for pedestrian dynamics," *Physical review E*, vol. 51, no. 5, pp. 4282, 1995.

[30] Helbing, D., Farkas, I., and Vicsek, T., "Simulating dynamical features of escape panic," *Nature*, vol. 407, no. 6803, pp. 487-490, 2000.

[31] Werner, T., and Helbing, D., "The social force pedestrian model applied to real life scenarios," In Proc. 2nd International Conference on Pedestrian and Evacuation Dynamics, pp. 17-26, 2003.

[32] Anders, J., "Pedestrian simulations with the social force model," Germany: Dresden University of Technology, 2004.

[33] Parisi, D. R., Gilman, M., and Moldovan, H., "A modification of the social force model can reproduce experimental data of pedestrian flows in normal conditions," *Physica A: Statistical Mechanics and its Applications*, vol. 388, no. 17, pp. 3600-3608, 2009.

[34] Matthias Luber, Johannes A. Stork, Gian Diego Tipaldi, and Kai O. Arras, "People tracking with human motion predictions from social forces," In Proc. IEEE International Conference on Robotics and Automation (ICRA), pp. 464-469, 2010.

[35] Zainuddin, Z., Thinakaran, K., and Shuaib, M., "Simulation of the pedestrian flow in the tawaf area using the social force model," *Simulation*, vol. 562, pp. 11179, 2010.

[36] Yanfei, Y., and Yonglin, M., "Simulation of Influence of Desired Velocity Distribution and Herd Effect on Pedestrian Evacuation," In Proc. Seventh International Conference on Computational Intelligence and Security (CIS), pp. 325-328, 2011.

[37] Gao-wei, Y., Chuang-qin, L., and Lu, M., "A novel swarm optimization algorithm based on Social Force model for multimodal functions," In Proc. 24th Chinese Control and Decision Conference (CCDC), pp. 849-854, 2012.

[38] Li, Z., and Jiang, Y., "A friction based social force model for group behaviors," In Proc. IEEE/WIC/ACM International Joint Conferences on Web Intelligence and Intelligent Agent Technology, vol. 2, pp. 1-8, 2012.

[39] Photchara Ratsamee, Yasushi Mae, Kenichi Ohara, and Tomohito Takubo, and Tatsuo Arai, "Modified social force model with face pose for human collision avoidance," In Proc, 7th ACM/IEEE International Conference on Human-Robot Interaction (HRI), pp. 215-216, 2012.

[40] Zhaofeng, L., and Yichuan, J., "A Friction Based Social Force Model for Group Behaviors," In Proc. IEEE/WIC/ACM International Conferences on Web Intelligence and Intelligent Agent Technology (WI-IAT), vol. 2, pp. 1-8, 2012.

[41] Yu Bai, Yi Xu, Xiaokang Yang, Qing Yan, "Measuring orderliness based on social force model in collective motions," In Proc. Visual Communications and Image Processing (VCIP), pp. 1-6, 2013.

[42] Yuan Gao, Peter B. Luh, Hui Zhang, and Tao Chen, "A modified social force model considering relative velocity of pedestrians," In Proc. IEEE International Conference on Automation Science and Engineering (CASE), pp. 747-751, 2013.

[43] Zhang, H., Jin, M., and Liu, H., "A modified social force model under different psychological conditions for room evacuation," In Proc. Improving Multimodal Transportation Systems-Information, Safety, and Integration, pp. 1262-1267, 2013.

[44] Teng Li, Huan Chang, Meng Wang, Bingbing Ni, Richang Hong, and Shuicheng Yan, "Crowded Scene Analysis: A Survey," *IEEE Transactions on Circuits and Systems for Video Technology*, vol. 25, no. 3, pp. 367-386, 2015.

[45] Ali, S., and Shah, M., "A lagrangian particle dynamics approach for crowd flow segmentation and stability analysis," In Proc. IEEE Conference on Computer Vision and Pattern Recognition, pp. 1-6, 2007.

[46] X. Zhu, J. Liu, J. Wang, W. Fu, and H. Lu, "Weighted Interaction Force Estimation for Abnormality Detection in Crowd Scenes," In Proc. 11th Asian Conference on Computer Vision, pp. 507-518, 2013.

[47] Sand, P., and Teller, S., "Particle video: long-range motion estimation using point trajectories," In Proc. IEEE Computer Society Conference on Computer Vision and Pattern Recognition, vol. 80, no. 1, pp.72, 2006.

[48] Horn, B. K. P., and Schunck, B. G., "Determining optical flow," *Artificial Intelligence*, vol. 17, vol. 1–3, pp. 185-203, 1981.

[49] Lucas, B. D., and Kanade, T., "An iterative image registration technique with an application to stereo vision," In Proc. 7th International Joint Conference on Artificial Intelligence, vol. 2, pp. 674-679, 1981.

[50] Nagel, H. -H., "On the estimation of optical flow: relations between different approaches and some new results," *Artificial Intelligence*, vol. 33, no. 3, pp. 299-324, 1987.

[51] Barron, J. L., Fleet, D.J., and Beauchemin, S. S., "Performance of optical flow techniques," *International Journal of Computer Vision*, vol. 12, no. 1, pp. 43-77, 1994.

[52] Kratz, L., and Nishino, K., "Tracking with local spatio-temporal motion patterns in extremely crowded scenes," In Proc. IEEE Conference on Computer Vision and Pattern Recognition, pp. 693-700, 2010.