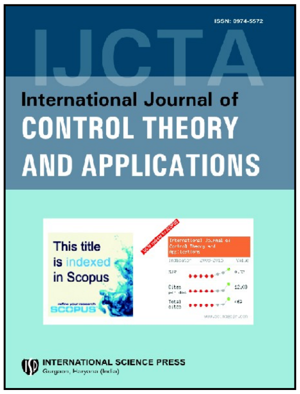

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Real Time Analysis of Video Behaviour Profiling for Detection of Abnormal Activity in Frames

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Abstract: The field of analyzing Video Behaviour profiling is very keen and distinct part in the area of Computer Vision and Video signal processing. The two main attributes of this field are Human Action Recognition (HAR) and Abnormal Activity Detection (AAD). Various researchers proposed several algorithms for HAR and AAD, since the analysis of video behaviour profile has numerous applications. This paper aims to detect the frames of abnormal activity in the surveillance video using combination of Optical flow vectors with morphological operation on the foreground pixel data. Prior to extraction of foreground pixel data, contrast adjustment applied to the frames for robust identification of motion based pixels only. This novel concept further uses the threshold of pixel intensity values in terms of motion and its continuity over a period of time to identify abnormal activity in consecutive frames. The proposed algorithm is computationally efficient in detecting abnormal activity frames, which is an attractive feature for real time applications.

Keywords: Anomaly Detection, Optical Flow, Motion Detection, Morphological Operation

1. INTRODUCTION

In general, human beings encounter abnormal events in daily life and can able to identify them with much ease and accuracy, such as disobedience of traffic rules, unexpected crowd in particular areas, the sudden collision of vehicles, stealing of objects etc. The reason behind this fact is, the human being can extract specific features of a particular a scene, huge experience (Training) of normal events and have the distinguishing (classification) capability. The similar extraction of abnormal activity based on video data by machine is very critical being one-to-one mapping of human intelligence into machine based algorithm is very complex. Various researchers have proposed several algorithms to detect abnormality in video frames, since this challenging task has several applications, such as identifying defective item from bulk production of factory outcome, health based applications to identify anomalies in scanned reports, security based applications to identify anomalies in surveillance video at sensitive locations and many more.

1.1. Related Work

The Survey Paper [1] pertaining to the domain of abnormal activity detection gives a comprehensive outline about point and contextual anomalies, with main focus on challenging issues like robustness and computation time of the algorithm. The definition of anomaly is always application oriented and has some degree of ambiguity as visual behaviours are generally complex. Much of the work is addressed by the research community to deal with the problems of poor video quality, occlusion, illumination variations and complex backgrounds. Another survey paper [2] gives exclusive overview of state-of-the-art developments of behaviour recognition algorithms for transit visual surveillance applications. Since, video is a sequence of images, Image-based anomaly detection technique was proposed [3] using network measurement approach that can simultaneously detect, identify anomalous traffic and the effectiveness was compared with classical detection theory based on the Neyman-Pearson test.

The anomaly in video based on group activity is modelled by moving and deforming shapes, is proposed by the researchers Vaswani *et al.* [4]. A continuous state hidden Markov Model [4] and Infinite hidden Markov model [5] are used to distinguish the anomalous activities in the video. Spatio-temporal features are configured to detect abnormal activities, especially the video based on crowded scenes is an interesting study proposed by various researchers [6] [7] [8] [9] in this domain. Object tracking with the help of colour modelling is used to detect anomaly based on deliberate object dropping at public places is an interesting study [10]. The features extracted by trajectory information is used to define event analysis module to identify suspicious event is proposed by Lee and Nevatia [11]. Trajectory clustering with Continuous hidden Markov model is proposed as a method for abnormality detection in traffic surveillance video at intersections [12]. The paper [13] addresses abnormality detection using combination of Gaussian Process, extreme value theory and divergence measurement. The feature representation of an anomalous event is detected by joint sparsity model is one of the recent approach proposed by Mo *et al.* [14].

1.2. Motivation for the work

The existing methods for Abnormal Activity Detection (AAD) are quite appreciable and interesting. But most of the methods are complex in extracting the features of anomaly. This makes the algorithm takes more computation time and not suitable for real-time applications. So our intention is to propose as simple method as possible to reduce the computation time and robust as well in detecting anomalous events of a given video.

The rest of the paper is organized as follows. Proposed algorithm and the methodology are explained in section 2. The flow diagram of the proposed methodology is given to easily interpret step by step understanding of the algorithm. The results along with corresponding discussions to appreciate the proposed method are presented in section 3. Concluding remarks are given in section 4.

2. PROPOSED ALGORITHM

The basic steps involved in the formulation of the proposed methodology are given as follows. The surveillance video of traffic and standard crowd video sequence are taken with frames of normal as well as abnormal event/activity. The surveillance video considered is having frames with normal traffic flow and collision of a car with a person is treated as frames of abnormal activity. Another video considered is a UCSD anomaly detection dataset. In this dataset, the normal frames having a pedestrian motion pattern only, whereas abnormal frames having non-pedestrian motion pattern as well such as cycle, biker etc.

The block diagram of the proposed methodology is explained in Figure1. Initially, the entire video is converted into grayscale images (frames). Contrast adjustment is applied over the set of frames, so that the noise in the frames is minimized and the images are restored with sufficient PSNR values. This makes the algorithm more robust in extracting motion based pixels.

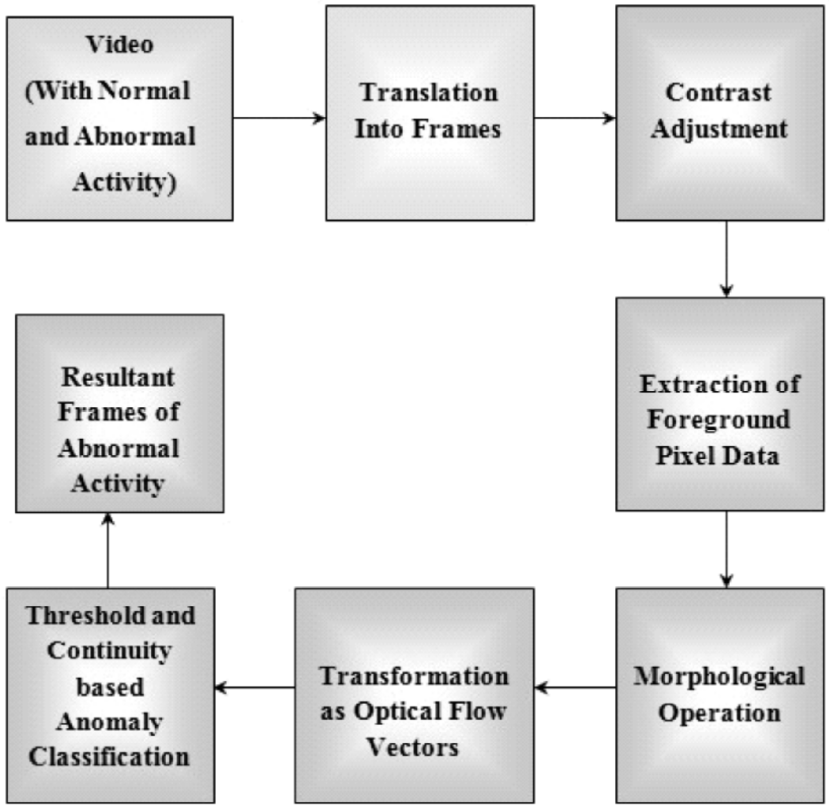

Figure 1: Flow Diagram of Proposed Methodology

The foreground pixels are extracted using Gaussian Mixture Modeling (GMM) algorithm. The purpose of using GMM is to retain only the pixels that have a relative change in the position from the previous frame to the current frame. GMM is superior to other foreground extraction models in terms of motion detection. Morphological operation (erosion and dilation) is performed to efficiently represent the pixel data connected in an optimized fashion. The shape 'Disk' is considered as a structural element in detecting the foreground objects.

Now the significant operation known as the optical flow method is applied over the pixels in each frame. Optical flow, calculates the velocity for points within the images, and provides an estimation that, where points could be in the next image sequence. The magnitude as well as direction parameters of optical flow vectors are computed for the entire sequence of frames. The method used for computing optical flow is Lucas Kanade method. Then for each two consecutive frames, the direction and magnitude values of the optical flow vectors are evaluated using equation (1) and (2) given as,

$$mag = \sqrt{u^2 + v^2} \tag{1}$$

$$theta = \tan^{-1}\frac{v}{u} \tag{2}$$

Where u = horizontal component of optical flow vector

v = vertical component of optical flow vector

The optical flow equation (3) has a constraint that it has two unknowns u and v in terms of intensity values is given as,

$$\mathbf{I_x}\, u + \mathbf{I_y}\, v + \mathbf{I_t} = 0 \tag{3}$$

Where $\mathbf{I_x}$, $\mathbf{I_y}$ and $\mathbf{I_t}$ are the partial derivatives of intensity with respect to x, y coordinates and time 't' respectively.

From the above equation, a normal component of the flow can be obtained, the Lucas Kanade method is one such method which helps in removing this constraint. Lucas Kanade method treats the following two assumptions:

(i) In a sequence of images, any two consecutive images are separated by a small time constraint, that is, the object in the two images is not displaced much.

(ii) There are no illumination changes.

It solves the optical flow equations for all the pixels in the neighborhood of a given pixel since it assumes that optical flow is constant within the neighborhood of a given pixel.

Based on the data obtained in the form of magnitude of optical flow vectors, a simple approach is considered to distinguish the frames having normal or abnormal activity. AAD in each frame is classified by two parameters. The first parameter is, if the motion of the pixel is greater than the threshold (speed or magnitude of the vector) value, then it is identified as point anomaly. The second parameter is, if the point anomaly persists over a period of time or over a sequence of frames, then the frames are classified as abnormal activity frames. The binary classification of abnormal activity detection is simple and found more robust.

3. RESULTS AND DISCUSSIONS

The visual representation of abnormal activity frames from standard UCSD anomaly detection dataset is shown in Figure 2. The left side image of Figure 2 is the original frame, the centre image is the representation of moving objects based on velocity (motion) threshold is marked as foreground disks. The image showing pedestrian movement with 'cycle' as moving object is represented as an anomaly in the frame. 'Cycle' as an abnormal object in the frame can be easily visualized with the merger of three disks. The pedestrian motion is relatively slow compared to cycle motion is represented with individual disk which is based on threshold values. Most of the pedestrian motion is not represented by circles, since their motion is less than the threshold. The right side image of Figure 2 is showing corresponding optical flow vectors.

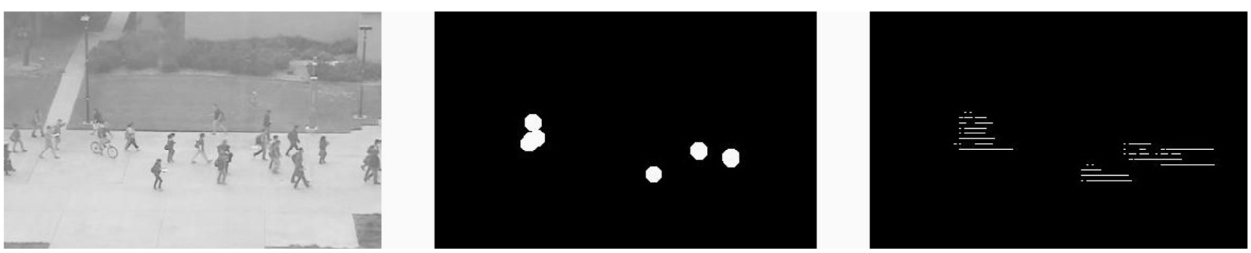

Figure 2: UCSD dataset image with corresponding foreground disk and optical flow vectors distinguishing cycle as abnormal object and pedestrians as normal objects

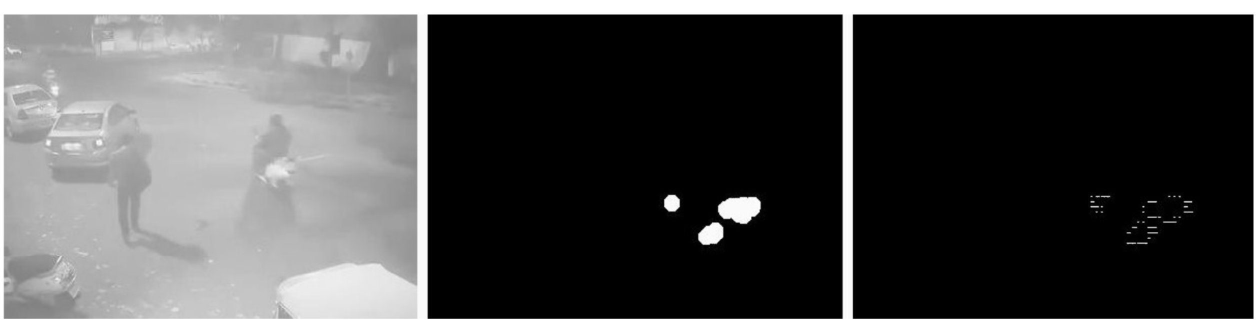

Figure 3: Normal activity frame, corresponding foreground motion disks and optical flow vectors

Figure 4: Abnormal activity frame, corresponding foreground motion disks and optical flow vectors

Figures 3 and 4 represent the normal activity frame and abnormal activity frame of the surveillance video respectively. In figure 3 normal traffic flow is observed with the motion of the pixels just above the threshold, only scooter velocity with noise is depicted as foreground disks and their corresponding optical flow vectors. Whereas, in Figure 4 very fast moving car is colliding with a person, resulting in an accident (abnormal activity) is clearly identified as merged disks over a period of time with corresponding optical flow vectors.

Table 1
Abnormal frame detection accuracy over different Video Dataset

Video	*Actual Abnormal Activity frames*	*Frames detected with abnormality by the proposed method*	*Detection Accuracy (%)*
UCSD Dataset 1	120	115	95.83
UCSD Dataset 2	120	112	93.33
Surveillance Video	60	58	96.66

The interesting results of video behavior profiling in Table 1 gives the abnormal activity detection accuracy of our proposed method. In all the three videos considered, out of 300 abnormal activity frames, 285 frames are detected correctly, which gives 95% accuracy.

Another significant parameter "processing time" is also well addressed by the proposed methodology and the statistics are provided in Table 2. We have implemented our methodology in Matlab R2013a using Intel(R) Core(TM) 2 Duo CPU 1.60GHz, 2 GB of RAM Laptop.

Table 2
Processing time for AAD over different Video Dataset

Video	*Duration of Actual Video*	*Processing time for AAD*
UCSD Dataset 1	5 Sec	5.79 Sec
UCSD Dataset 2	5 Sec	5.82 Sec
Surveillance Video	10 Sec	11.41 Sec

4. CONCLUSION

A simple method for abnormal activity detection based on morphological operation and Optical flow vectors is proposed. Threshold of pixel motion and duration of continuous intensity is considered to distinguish normal and abnormal activity in the frames. The algorithm found to be more robust in identifying abnormal activity frames. The algorithm runs over 2972 frames having 300 abnormal activity frames. The proposed method of video behavior profiling gives a promising 95% Abnormal Activity Detection (AAD) accuracy. The proposed algorithm also taking less computation time to detect normal and abnormal activity in video frames, suitable for real-time applications.

REFERENCES

[1] O. P. Popoola and K. Wang, "Video-Based Abnormal Human Behavior Recognition: A Review," *Syst. Man, Cybern. Part C Appl. Rev. IEEE Trans.*, vol. 42, no. 6, pp. 865–878, 2012.

[2] J. Candamo, M. Shreve, D. B. Goldgof, D. B. Sapper, and R. Kasturi, "Understanding transit scenes: A survey on human behavior-recognition algorithms," IEEE Trans. Intell. Transp. Syst., vol. 11, no. 1, pp. 206–224, 2010.

[3] S. S. Kim, A. L. N. Reddy, and S. Member, "Image-Based Anomaly Detection Technique/ : Algorithm , Implementation and Effectiveness," vol. 24, no. 10, pp. 1942–1954, 2006.

[4] N. Vaswani, A. Roy-chowdhury, and R. Chellappa, "'Shape Activity': A Continuous-State HMM for Moving / Deforming Shapes With Application to Abnormal Activity Detection," *IEEE Trans. Image Process.*, vol. 14, no. 10, pp. 1603–1616, 2005.

[5] I. Pruteanu-Malinici and L. Carin, "Infinite hidden Markov model for unusual-event detection in video," *IEEE Trans. Image Process.*, vol. 17, no. 5, pp. 811–822, 2008.

[6] M. Thida, S. Member, H. Eng, and P. Remagnino, "Laplacian Eigenmap With Temporal Constraints for Local Abnormality Detection in Crowded Scenes," vol. 43, no. 6, pp. 2147–2156, 2013.

[7] M. Bertini, A. Del Bimbo, and L. Seidenari, "Multi-scale and real-time non-parametric approach for anomaly detection and localization," Comput. Vis. Image Underst., vol. 116, no. 3, pp. 320–329, 2012.

[8] M. J. Roshtkhari and M. D. Levine, "An on-line, real-time learning method for detecting anomalies in videos using spatio-temporal compositions," Comput. Vis. Image Underst., vol. 117, no. 10, pp. 1436–1452, 2013.

[9] N. Li, X. Wu, D. Xu, H. Guo, and W. Feng, "Spatio-temporal context analysis within video volumes for anomalous-event detection and localization," Neurocomputing, vol. 155, no. June, pp. 309–319, 2015.

[10] M. Gangadharappa, Pooj Goel, Rajiv Kapoor "Anomaly Detection in Surveillance Video using Color Modeling," International Jjournal of Computer Applications, vol. 45, no. 14, pp. 1–6, 2012.

[11] S. C. Lee and R. Nevatia, "Hierarchical abnormal event detection by real time and semi-real time multi-tasking video surveillance system," *Mach. Vis. Appl.*, vol. 25, no. 1, pp. 133–143, 2014.

[12] Omer Akoz and M. E. Karsligil, "Traffic event classification at intersections based on the severity of abnormality," Mach. Vis. Appl., vol. 25, no. 3, pp. 613–632, 2014.

[13] M. Smith, S. Reece, S. Roberts, I. Psorakis, and I. Rezek, "Maritime abnormality detection using Gaussian processes," *Knowl. Inf. Syst.*, vol. 38, no. 3, pp. 717–741, 2014.

[14] X. Mo, V. Monga, R. Bala, and Z. Fan, "Adaptive sparse representations for video anomaly detection," IEEE Trans. Circuits Syst. Video Technol., vol. 24, no. 4, pp. 631–645, 2014.