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Human Crowd Anomaly Detection for Video Surveillance

[1] Shreekar Waghela, [2] Shreedarshan K,
[1][2] Ramaiah Institute of Technology, Bangalore, India

Abstract - **Video surveillance is very essential as threat and crime increases. In this project, a method is proposed in which the behaviour of crowd is detected without individual tracking of objects in a frame. This method is based on the motion intensity of the crowd which can be determined by accumulating all optical flow vectors of a frame. The abnormal crowd activity can then be detected by setting up a threshold to detect any sudden change in motion intensity.**

Index Terms— Anomaly Detection, Dynamic Threshold, Motion Intensity, Optical Flow

INTRODUCTION

Video surveillance is very essential as threat and crime increases. Camera based surveillance systems are installed in most of the places like office buildings, stadiums, traffic signals, residential area, railway platforms and airports. These security cameras require incessant human presence for monitoring the footage and if any anomaly is detected they inform the officials by issuing an alert. Since it is all done manually, it is essential they should be concentrated all the time. So, it is possible that a lack in concentration may result in an incident gone unnoticed.

To overcome this problem a system needs to be developed which can detect behaviour and then identify it as normal or abnormal. The main focus is on abnormal behaviour detection of crowd when state of motion of the crowd changes sharply in a short time and crowd running is an indicator of emergency. Guo [6] and Zhi [7] have done anomaly detection based on energy and static threshold, but neither of them has considered light intensity condition. So this paper aims to present a method to adapt to light conditions and detect sudden running of crowd based on optical flow and dynamic threshold.

In section II, related works will be introduced. In section III, a brief introduction of architecture is given. In section IV, we define the crowd motion intensity by estimating velocity of the crowd. In section V, we will introduce a method to calculate dynamic threshold and detect abnormality based on it. In section VI, we analyze experimental results. In last section VII, we summarize the conclusion and present clues for future research work.

II. RELATED WORK

Abnormal crowd behaviour detection can be divided into two categories: one is based on individuals and other is entire crowd. In individual based category, the crowd is considered as a collection of individuals, so it is necessary to do segmentation and track trajectories, but this approach is affected by heavy occlusion in a crowd scene. The latter one regards the crowd as an entirety in analysis of medium to high density scenes. Instead of tracking individuals, this approach extracts features of the crowd to represent the state which is suitable to crowd scene. There are different methods to detect the abnormality: Histogram of Oriented Tracklets [1], compact video synthesis [2] and optical flow manifolds [3]. There are five behaviours of crowd based on which abnormality is defined: lane, blocking, bottleneck, fountainhead and ring [5]. Guo [6] and Zhi [7] give a concept of energy and static threshold to detect anomaly but they consider only constant light condition. Yang[4] gives a method to calculate dynamic threshold which is adaptive to changing light conditions. Inspired by their work, this paper is trying to improve on the model by providing a method to detect anomaly for different light conditions using foreground extraction and dynamic threshold.

III. SYSTEM ARCHITECTURE

In our paper, we adopt a method based on foreground extraction to deal with changing light conditions and dynamic threshold for automatic detection of abnormality. The system architecture is shown in Figure 1, and the parts of the architecture are: image pre-processing and foreground extraction, optical flow, motion intensity estimation and dynamic threshold detection.

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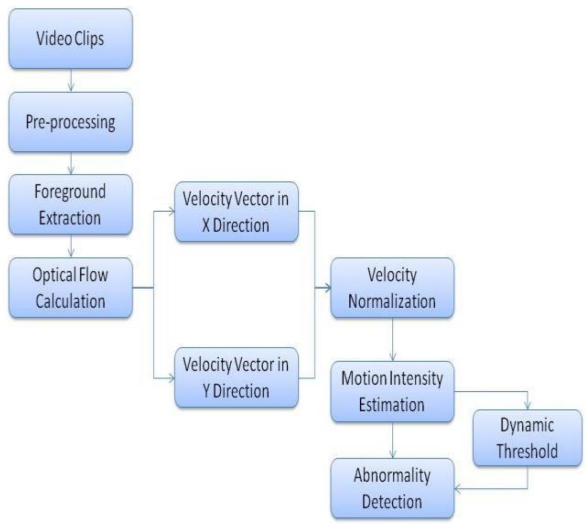


Fig.1 Flow Chart of System Architecture

In implementation of foreground extraction, the method used is frame differencing. One frame is considered as background and that background is subtracted from other frame to obtain the foreground. An adaptive background approach has been used, so that the background changes according to the current frame. The obtained difference image is then converted to binary image as shown in Figure 2. These binary images are then used to track moving objects by applying optical flow on them. Next part of the architecture is to determine crowd motion intensity based on velocity vectors obtained from optical flow. The last part is to determine dynamic threshold to detect anomaly in a crowded scene.

Fig.2 Original Frame (a); Foreground Extracted Frame (b)

IV. MOTION INTENSITY ESTIMATION

A. Optical Flow Calculation

Optical flow is the pattern of apparent motion of objects, surfaces and edges in a visual scene caused by relative motion between an observer and the scene. It is used to determine the motion of the objects in two frames at time t (previous frame) and t + dt (current frame) [5]. We consider foreground extracted frames and calculate optical flow to estimate motion of crowd shown as in Figure 3. With changing motion of objects in two frames, we can obtain motion vector in 2-D space and compute velocity in X- axis and Y- axis.

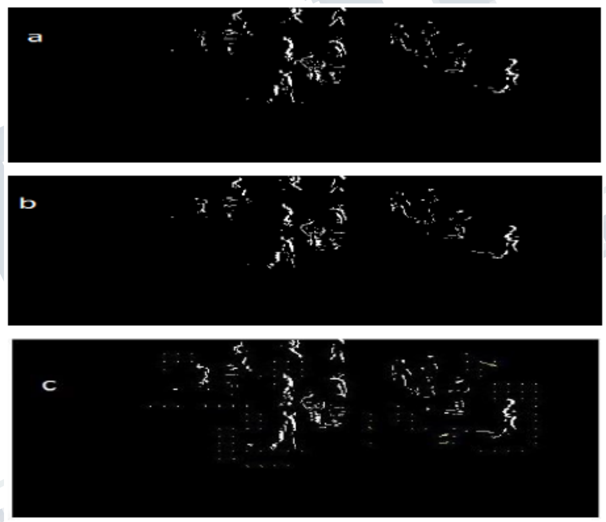


Fig.3 Current Frame (a); Previous Frame (b); Optical Flow (c)

B. Velocity Normalization

As we can see in Figure 4, the distance between A and B is larger than that of A' and B' in the 2-D image plane of the camera, however, they are the same in real 3-D world. So we can know that the closer to the camera the larger of the same distance which results in a phenomena that people who are closer to the camera run faster than the further ones though they are of the same speed in real 3-D world. To estimate the velocity of the crowd more accurately, we had better normalise the velocity to diminish this distortion. So we can introduce a weight related to the coordinate of the point or use other geometric methods to do modification.

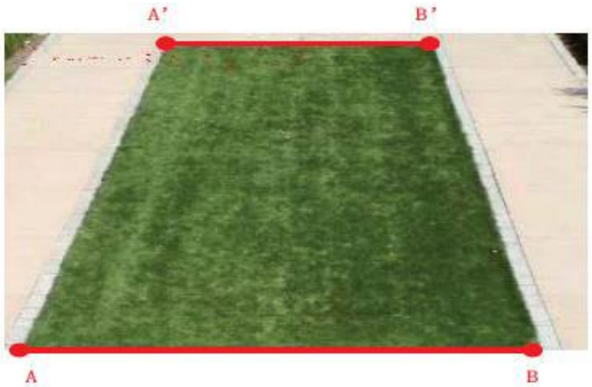


Fig.4 Pinhole perspective projection distortion

C. Estimation of Motion Intensity

Inspired by anomaly detection based on the concept of energy in [4], [6] and [7], we define motion intensity of a frame by kinetic energy as follows:

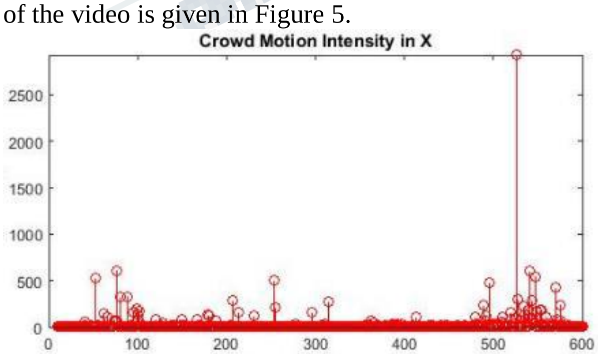
$$E_k = \sum m_{i,j} v_{i,j}^2 \qquad (1)$$

Where vi,j is the velocity of the point with coordinate (i, j) and mi,j is the weight to diminish the distortion mentioned in part B. Then the energy of each point (i, j) is accumulated to built whole energy of a frame. We can obtain the velocity in X- axis and Y- axis called as vx and vy. Based on this, we can calculate the real velocity and the motion direction as follows:

$$v = \sqrt{V_x^2 + v_y^2} \qquad (2)$$

$$\theta = \arctan(\frac{v_y}{v_x}) \qquad (3)$$

The values vx and vy can be calculated by the output of optical flow velocity vectors obtained from Lucas-Kanade algorithm. The motion intensity of each frame of the video is given in Figure 5.



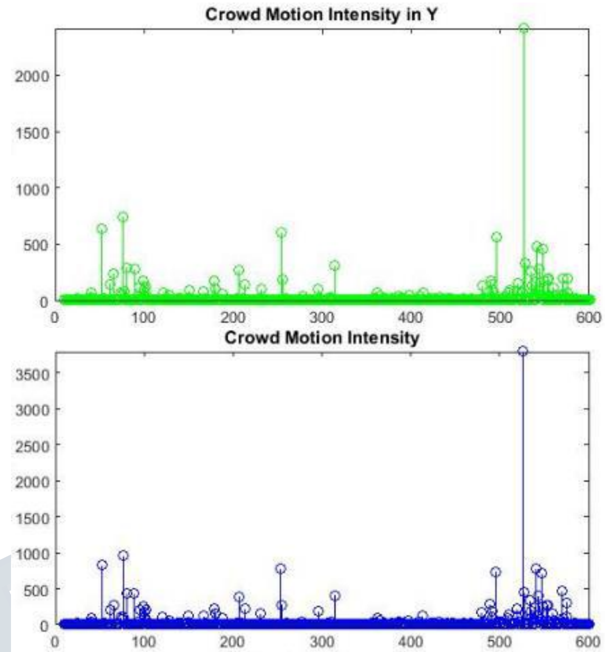


Fig. 5 Motion Intensity of each frame

V. ABNORMAL BEHAVIOUR DETECTION

A. Crowd Motion Intensity in a Crowd Scene

We all know that people running in a crowded area is an indicator of emergency such as, explosion or stampede. Motion Intensity also referred as Crowd Motion Intensity (CMI) defined by kinetic energy can describe the running activity well. When people walk normally the CMI will be relatively steady, but when people suddenly start running CMI will jump to a higher value as shown on Figure 5. So we can detect the abnormality in crowd motion by detecting the whether the people are running suddenly. However, optical flow is sensitive to light conditions. To overcome this problem we apply optical flow to the foreground extracted from the actual frames. This is possible as foreground is extracted only when there is motion in two consecutive frames. Figure 6 shows frames with constant light conditions. The normal level of CMI for constant light conditions can be separated from abnormal level by a static threshold. The CMI of constant light condition frames is shown in Figure 7.

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Fig. 6 Frames of scene with constant light condition

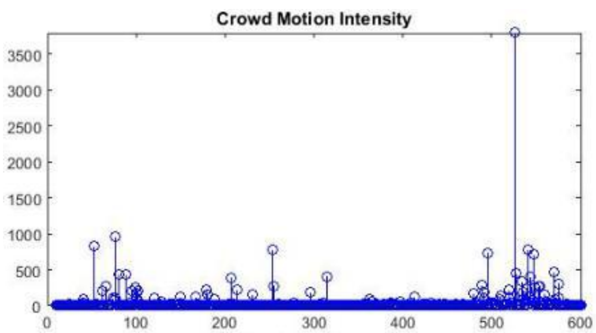

Fig. 7 Crowd Motion Intensity of each frame

Figure 8 shows frames with slightly changed light conditions (dim light condition). The CMI for this condition is shown in Figure 9.

Fig. 8 Frames of scene with dim light conditions

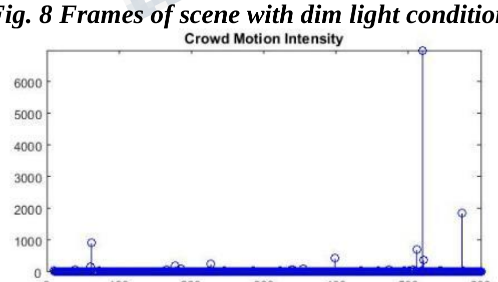

Fig. 9 Crowd Motion Intensity of each frame

From Figure 7 and Figure 9, we can see that though optical flow is sensitive to light conditions the CMI estimated is appropriate as optical flow is applied on foreground of the frames.

B. Methodology for Dynamic Threshold Calculation

In constant light condition, The CMI obtained is as in Figure 7 and we can simply assign a static threshold to recognise abnormal level from the normal level to detect anomaly. But in such case we have to assign a threshold to detect anomaly. So overcome this, an algorithm has been designed to automatically select a threshold to separate normal level and abnormal level, this is called dynamic threshold (DT). The methodology for DT calculation is shown as a flow chart in Figure 10. The method consists
of following steps:
Step 1: Initialize DT and calculate CMI
Step 2: Compare CMI with DT*(1 + α)
Step 3: Get result value base on step 2
Step 4: Loop to update DT according to result value
We analyze the behaviour frame by frame and hence DT is initialized by calculating CMI of the first frame. Number of frames is denoted by N. A parameter α is used to compare CMI with DT. The result of the comparison of step2 is defined as follows:

$$Result = \begin{cases} 0 & if\ CMI > (1+\alpha)DT \\ 1 & else \end{cases} \qquad (4)$$

Based on the result, we can calculate and update DT according to the flow chart shown in Figure 10.

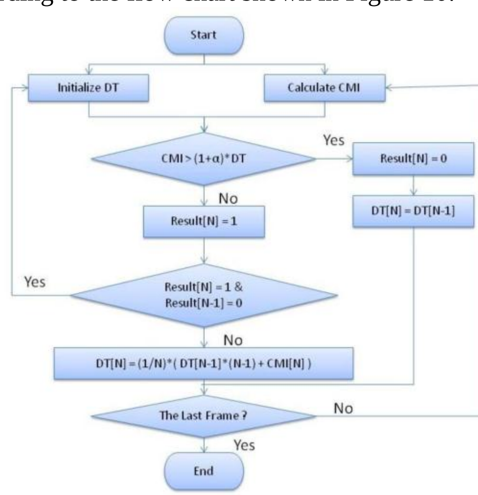

Fig. 10 Flow chart for Dynamic Threshold Calculation

From above, we can see that if result is 0, then the anomaly is likely to happen and the DT is kept same as previous. If condition for DT is not satisfied, then current and previous results are compared and DT is updated according to the formula as shown in flow chart. The application of algorithm gives anomaly detection as shown in the Figure 11.

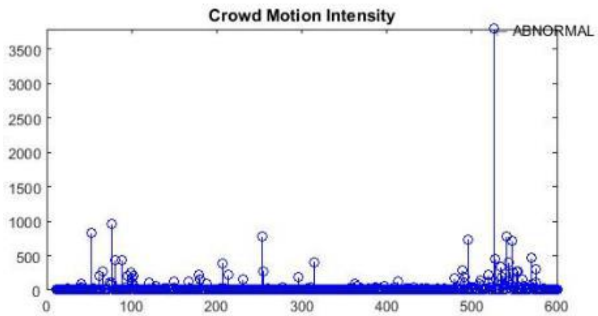

Fig. 11 Anomaly detection using threshold algorithm

VI. EXPERIMENTAL RESULTS

The approach is tested on the UMN Dataset which is the publicly available dataset of normal and abnormal crowd videos from University of Minnesota [9]. Figure 12 shows sample frames of these videos. Each video starts with normal behaviour with some sequences of abnormal behaviour inserted in the video frames. People are wandering in normal sequences and running suddenly at a time. In Figure 12, image (a) and (b) are in constant light condition and light condition slightly changes in (c) (d) and in images (e) and (f) the light conditions are very dim. The images (a),(c),(e) show normal behaviour and images (b),(d),(f) show abnormal behaviour.

The resolution of the video clips is 320*240, and we define parameter $\alpha = 0.3$. As shown in Figure 11 the anomaly starts at the frame in which the CMI is very high and it is detected as the CMI exceeds DT according to dynamic threshold algorithm.

Fig. 12 Sample frames of normal and abnormal behavior

VII. CONCLUSIONS AND FUTURE WORK

In this paper, we present a method for anomaly detection using energy model. Our method is based on extraction of foreground from video frames and optical flow, estimating energy of the crowd, i.e., motion intensity which is obtained by using velocity vectors from optical flow. A dynamic threshold algorithm is used for automatic detection of abnormality, which adapts according to the energy levels in the video and also adapts to the changing light conditions. In future, we will try using other methods to estimate motion intensity of crowd and also descriptors other than optical flow.

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