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CROWD BEHAVIOUR ANALYSIS AND CLASSIFICATION USING GRAPH THEORY

Najmuzzama Zerdi[1], Dr. Subhash Kulkarni[2], Dr. V.D.Mytri[3]
[1]Research Scholar, H.O.D (E&CE), K.C.T.E.C., Gulbarga. E-mail:zerdi_2006@yahoo.co.in
[2] Guide, Prof. & H.O.D. (E&CE), P.E.S.I.T, Bangalore. E-mail:sskul@pes.edu
[3] Co-Guide, Principal, A.I.E.T, Gulbarga, E-mail:vdmytri.2008@rediffmail.com

Abstract: **Crowd analysis becomes the most active-oriented research in computer vision .now a days, a wide attention has been paid to crowd control and management in the intelligent video surveillance area. In this paper, Graph theoretic approach based Crowd Behavior Analysis and Classification System method is used to identify crowd behaviors in visual screen. We focus on the motion trajectories to observe the crowd behavior of the personnel in the crowd and Optical flow methods are used to acquire the streak lines and path lines of the crowd personnel trajectories. Streak flow is obtained by combining path line and streak line. The frames of the surveillance videos are analyzed using graph theoretic approaches. The convincing results obtained from the experiments on datasets demonstrate that the proposed method obtains for crowd behavior analysis.**

Key Words: **Video surveillance, Crowd motion, Crowd Behavior, Optical Flow, Streak Lines, Path Lines, Streak line Flow, Graph Theory, Threshold**

1. INTRODUCTION

Videos of crowd scenes present challenging problems in computer vision. High object-densities in real-world situations make individual object recognition and tracking impractical; understanding the crowd behaviors, without knowing the actions of individuals, is often advantageous. Automated detection of crowd behaviors has numerous applications, which may help avoid unnecessary crowding and discovery of abnormal behaviors or flow, which may help avoid tragic incidents. .The need for automated systems to classify the movements of crowds or detect abnormal activity can be considered as an open research issue. A crowd can be considered as a collection of people distributed over the region of interest. Tracking of human activity or personnel counting within video surveillance systems has been researched upon for some time now. The open research issues that exist and require attention with respect to crowd analysis can be listed as modeling or knowledge extraction from crowd patterns [7-8] and crowd behavior analysis. Limited work is carried out to classify the behavior of crowds in surveillance systems. The research work presented in this paper introduces the Graph theoretic approach based Crowd Behavior Analysis and Classification System. To achieve accurate classification results the behavior of the personnel in the crowd needs to be analyzed first. The behavior of the personnel in the crowd can be analyzed based on the motion or trajectory activities observed. Based on the behavior of the personnel analyzed, it can be classified into normal or abnormal activity. Abnormal activity detection is achieved by observing unusual behavior of personnel or group of personnel within a crowd. Activities like instantaneous disbursement, sudden convergence or fighting are classified as abnormal activities. The work carried out so far by researchers, primarily concentrates on analysis of activities amongst a few personnel present in the crowd only, and do not take into account the inter personnel activities for classification. To overcome this Graph theoretic approach based Crowd Behavior Analysis and Classification System drawback the presented in this paper considers inter personnel activities for analysis. The inter personnel activities are monitored through the motion vectors observed. To obtain the behavioral vectors of personnel in the crowd video an optical flow is initially computed. Based on the optical flow the path lines and streak lines are obtained. The path lines, streak lines are used to derive the streak flow vectors which define the potential and personnel flow. Every frame of the video is analyzed using graph theoretic approaches. The proposed method considers each frame as a graph with sub graphs. All the frames are analyzed and the cumulative variance is computed. the cumulative variance is greater than a threshold the activity of the personnel in the crowd is classified as an abnormal activity.

The rest of this paper is organized as follows, Section two discusses the literature review. The Graph theoretic approach based Crowd Behavior Analysis and Classification System is discussed in section three of the paper. The experimental study conducted to evaluate the performance of the Graph theoretic approach based Crowd Behavior Analysis and Classification System is discussed in the penultimate section of the paper. The conclusion and future work is discussed in last section of this paper.

I. Graph theoretic approach based crowd behavior analysis and classification system

A. system model

In this paper, we are considering a surveillance video $F \times n$. The video represents a set of F frames and the dimension of each image n is $a \times b$ pixels. Let us consider a frame P at the t^{th} time instance and $P \in F$. Similarly the frame at the $(t+1)^{th}$ time instance is represented as Q .The frame $F^1 \in F$ is split into a number of blocks and a mesh based structure is created for computational ease. Let the set $\mathrm{I} \subset \mathrm{J}^2$ represent the crowd personnel to be observed in the surveillance video space J^2. The set I consists of M personnel. The trajectory of the m^{th} personnel i.e. $m \in M$ at the time instance $\dot{t}$ can be represented as $m\ (t{:}\, t_{\dot{t},} m_{\dot{t}})$. At the initial instance i.e. $\dot{t} = 0$ the trajectory is represented as $m\ (t{:}\, t_{0,} m_0)$. The trajectories is utilized for optical flow $\bar{J}$ computations. From the optical flows the streak lines Λ and path lines K of the personnel in the crowd are computed frame wise. The streak flow Γ is then derived which is used for analysis. For analysis a graph theoretic approach is adopted in the $GCBACS$. Each frame is considered as a graph $\mathbb{G}$ and analysis is

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carried out on the similarity and deviations are observed. Cumulative variance is computed considering all the previous frames and the current frame. If the variance is greater than the threshold then abnormal activity is said to be detected. The proposed in this paper can be understood based on the model shown in Figure 1.

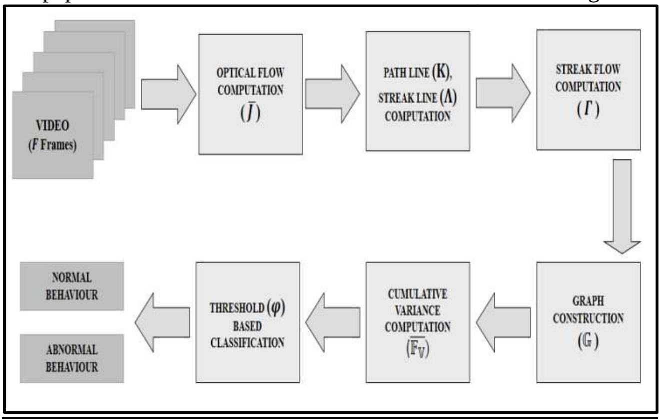

Figure 1: model overview

B. Optical flow computation

In Graph theoretic approach based Crowd Behavior Analysis and Classification System the Lucas & Kanade based methodology is used to compute the differential optical flow of the crowd vectors. The optical flow enables trajectory detection of personnel in the crowd. Let the velocity field defined over the set be represented as . The velocity satisfies the continuity in time and continuity in space domain to obtain smooth optical flows. To achieve optical flow computation a hierarchical graph structure is considered to represent the video . Let the levels of the graph be defined as . If represents the velocity then the optical flow residual vector is used to minimizes the function vector . Similarly the matching function can be minimized using the residual vector . The primary guess for the level of the optical flow is denoted as . The value of is obtained by optical flow computations from to . The frame and can be represented on the basis of the optical flows computed at all the levels and is described as

(1)

(2)

Where are two integer values and and represent the previous two frames. Based on the above equations it can be observed that there exist a domain definition difference between and . The optical flow representation of the frame is defined over the window size instead of using . Consider that the displacement vector is and image position vector is . The vector minimizes the matching function . The function is defined as

(3)

An iterative Lucas –Kanade method is adopted to solve the function and is represented as

(4)

Note that – is the temporal frame image derivative at the point . The point is defined as

(5)

The derivative at is defined as

(6)

In Equation 5, is the gradient vector and can be defined as

(7)

The derivatives and can be computed directly from the image in the , which is a neighborhood of the point independently from the next image . The derivative images satisfy the expression and can be defined as

(8)

(9)

(10)

(11)

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Considering $\bar{J}_{opt}$, it is evident that $P\,(a,b)$ contains information of the gradients in the a and b direction of N. Let $\mathcal{W}$ represent the number of iterations required and $\mathcal{W} \geq 1$. Based on the optical flow computations from $1,2,3,\cdots(\mathcal{W}-1)$ the initial guess $\bar{J}^{\,\mathcal{W}-1}$ for pixel displacement $\bar{J}$ is obtained. The initial guess is given as $\bar{J}^{\,\mathcal{W}-1} = [J_a^{\mathcal{W}-1}\, J_a^{\mathcal{W}-1}]^T$. If $Q_{\mathcal{W}}$ represents the new image based on $\bar{J}^{\,\mathcal{W}-1}$, provided $\forall(a,b)\,\epsilon\,[p_a - \omega_a, p_a + \omega_a] \times [p_b - \omega_b, p_b + \omega_b]$ then

$$Q_{\mathcal{W}}(a,b) = Q(a + J_a^{\mathcal{W}-1}, b + J_b^{\mathcal{W}-1}) \quad (12)$$

Using the optical flow methodology in $GCBACS$ the residual pixel trajectory vector and mismatch vectors are obtained.

C. Streak line flow computation

In Graph theoretic approach based Crowd Behavior Analysis and Classification System the use of streak flow to observe the trajectory of the personnel in the crowd is considered as the streak flow methodology enables instantaneous change observation when compared to particle flows.

Let us consider a particle at position N in the t^{th} time instance, present in the F frame and it is represented as $(a_F^N(t), b_F^N(t)\,)$. The advection of the particle is achieved by

$$a_F^N(t+1) = a_F^N(t) + J_a(a_F^N(t), b_F^N(t), t) \quad (13)$$

$$b_F^N(t+1) = b_F^N(t) + J_b(a_F^N(t), b_F^N(t), t) \quad (14)$$

Where J_a,J_b are obtained from the optical flow vectors. For all the frames F and time $t = 1,2,3 \ldots T$ using particle advection we can obtain a vector matrix.. In this paper $\mathrm{K}^N(t,T)$ is used to represent the path lines. Based on the streak lines the behavior of the personnel in obtained. Therefore, the streak flow is computed and is defined as

$$\Gamma_s = (J_a^s, J_b^s)^T \quad (15)$$

The streak line computation is realized by integrating the optical flows $\bar{J}$ computed and forming extended particles. To compute Γ_s , J_a^s and J_b^s have to be computed. let us consider a vector $\mathcal{J}_a = [J_a^l]$ to obtain the streak flow in the a direction. The extended particle E_l has three pixels as its neighbors which forms a triangle. J_a^s is considered as the interpolations of the neighboring pixels and is computed by

$$J_a^l = a_1 J_a^s(i_1) + a_2 J_a^s(i_2) + a_3 J_a^s(i_3) \quad (16)$$

Using the interpolation method the parameters $J_a^s(i_1)$,$J_a^s(i_2)$ and $J_a^s(i_3)$ are obtained. For all the vectors in $\mathcal{J}_a$ and based on Equation 16 we can state

$$\mathfrak{L}\, J_a^s = J_a^l \quad (17)$$

Where a_{fn} are the elements of the matrix $\mathfrak{L}$ .Using J_a^s and J_b^s the streak flow Γ_s is obtained.

D. Graph Therotic Mechanism

Let us consider a graph $\mathbb{G}\,(\mathbb{V},\mathbb{E})$ obtained from the streak flow Γ_F . The vertices of the graph are the number of pixel a vector observed and is defined as

$$\mathbb{V} = \{\mathcal{v}_1, \mathcal{v}_2, \ldots \mathcal{v}_n\} \quad (18)$$

The edges of the graph $\mathbb{G}$ can be represented as

$$\mathbb{E} = \{e_1, e_2, \ldots e_m\} \quad (19)$$

The streak flow Γ computed represents a planar field, and $\Gamma = \Gamma_c + \Gamma_r$ based on the decomposition defined by Helmholtz. Γ_c is the incompressible part and Γ_r is the irrotational part of the vector field. The stream function α and the velocity potential function β are computed using Fourier Transforms as described in [22]. The functions α and β are defined as

$$\alpha(a,b) = \alpha_0 + \left(\frac{1}{2} \times \int_0^b \left(J_a^c(a,s) + J_a^c(0,s)\right) ds\right) - \left(\frac{1}{2} \times \int_0^a \left(J_b^c(s,b) + J_b^c(s,0)\right) ds\right) \quad (20)$$

$$\beta(a,b) = \beta_0 + \left(\frac{1}{2} \times \int_0^a \left(J_a^r(s,b) + J_a^r(s,0)\right) ds\right) + \left(\frac{1}{2} \times \int_0^b \left(J_b^r(a,s) + J_b^r(0,s)\right) ds\right) \quad (21)$$

The function α provides details of the steady motion vectors and β provides the details of the random motion changes detected. By combining the α and β vectors the potential functions of the video frame is computed and the edge set $\mathbb{E}$ can be defined as

$$\mathbb{E} = \{\alpha\,, \beta\} \quad (22)$$

To detect abnormal behavior analysis of consecutive frames is considered i.e. graph $\mathbb{G}_{t-1}$ and graph $\mathbb{G}_t$. The local differences in the sub sets are measured to analyze the finer movements in the graphs and is computed using

$$\mathfrak{D} = \left(\frac{f\left(\mathbb{G}_{t-1}^{Sub}, \mathbb{G}_t^{Sub}\right)}{(f_{Max} - f_{Min})}\right) \quad (23)$$

Where $f(x)$ is a function that defines the matching between the sub sets $\mathbb{G}_{t-1}^{Sub}$ and $\mathbb{G}_t^{Sub}$. Where γ is a predefined integer. The cumulative variance observed till the F^{th} frame can be defined as

$$\overline{\mathbb{F}_{\mathbb{V}}} = \sum_{x=1}^{F} \mathbb{F}_{\mathbb{V}} \quad (24)$$

If the value of the cumulative variance is greater than a predefined threshold φ then abnormal event is detected in the video and it is assigned the class 1 else 0. The classification can be defined as

$$\begin{cases} F_{Class} = 0\,, & If\ \overline{\mathbb{F}_{\mathbb{V}}} < \varphi \\ F_{Class} = 1\,, & If\ \overline{\mathbb{F}_{\mathbb{V}}} \geq \varphi \end{cases} \quad (25)$$

III. Results and Discussion

This experiment evaluates the performance of the Graph theoretic approach based on Crowd Behavior Analysis and Classification

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System and on Scenario 1 and Scenario is shown in Figure 2.In the figure the use of bars is considered to represent the results where the green bars represent normal crowd activity and the red bars represent abnormal crowd activity. From the figure it is clear the proposed Graph theoretic approach based Crowd Behavior Analysis and Classification System exhibits better accuracy when compared to the system proposed i.e. . The nearly follows the ground truth bar shown in the figure.. The misclassification is reduced as the proposed method adopts the streak line flow to capture the behavior of personnel in the scenario videos considered. Based on the results it can be concluded that the proposed in this paper can be efficiently adopted for crowd behavior study and analysis under varying conditions i.e. indoor and outside scenarios.

Figure 2: Comparison results of crowd behavior recognition and classification for sample videos in Sequence 1 and Sequence 2

The results are evaluated using receiver operating characteristic curves ( ). The curve obtained for scenario 1, scenario 2 is shown in Figure 3 and Figure 4.. Considering Scenario 1 it is observed that the area under the curve for is 0.89 and 0.68 for the . The area under the curve for and is 0.97 and 0.79, considering scenario 2. Both and exhibit better results when the indoor scenario 2 is considered as the motion of the personnel in this video is relatively uniform. The motion trajectories of personnel in scenario 1 is erratic and random. In both the scenarios the area under the curve of is more than the area under the curve for .

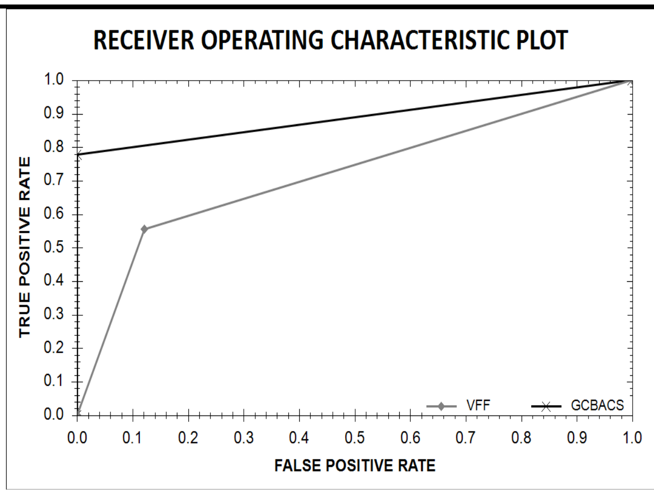

Figure 3: ROC Curves for Crowd Activity Classification based on and for Scenario

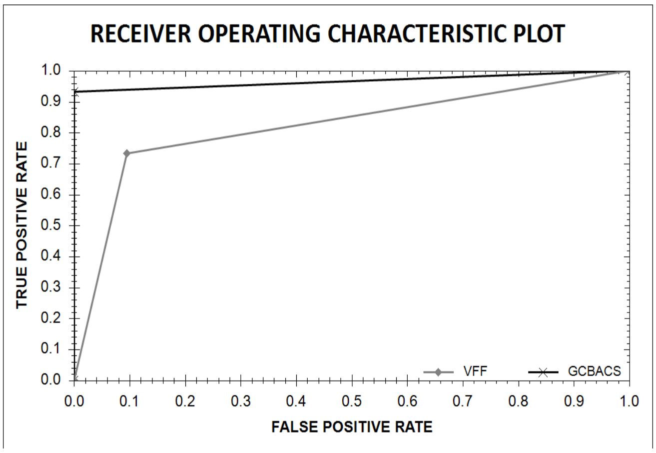

Figure 4: ROC Curves for Crowd Activity Classification based on GCBACS and VFF for Scenario

IV. Conclusion and Future work

In this paper, we introduce Crowd Behavior Analysis and Classification System for surveillance video crowd behavior and analysis. The Crowd Behavior Analysis and Classification System considers the use of streak flows to attain the crowd personnel behavior. The streak flows are obtained from the streak lines and path lines. Optical flow methods are used to obtain the streak lines. The potential field variations captured by the streak flows are analyzed using graph theoretic approaches. A threshold based scheme is adopted to classify the cumulative variation observed in all the frames of the video. The crowd activity is classified as normal and abnormal behavior based on the inter personnel activity. The experimental results presented in this paper validate that the proposed method can be utilized for analysis of indoor and outdoor crowd surveillance videos. The results validate that the proposed method outperforms the existing methods used for crowd behavior analysis and classification. The future of the research work presented in this paper is to validate the performance of in varied datasets.

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