Global Journal of Computer Science and Technology: F
Graphics & Vision
Volume 14 Issue 1 Version 1.0 Year 2014
Type: Double Blind Peer Reviewed International Research Journal
Publisher: Global Journals Inc. (USA)
Online ISSN: 0975-4172 & Print ISSN: 0975-4350

# Crowd Behavior Analysis and Classification using Graph Theoretic Approach

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*GJCST-F Classification: G.2.2*

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# Crowd Behavior Analysis and Classification using Graph Theoretic Approach

Najmuzzama Zerdi [α], Dr. Subhash S Kulkarni [σ], Dr. V .D. Mytri [ρ] & Kashyap D Dhruve [ω]

*Abstract-* Surveillance systems are commonly used for security and monitoring. The need to automate these systems is well understood. To address this issue we introduce the Graph theoretic approach based Crowd Behavior Analysis and Classification System ($GCBACS$). The crowd behavior is observed based on the motion trajectories of the personnel in the crowd. Optical flow methods are used to obtain the streak lines and path lines of the crowd personnel trajectories. The streak flow is constructed based on the path and streak lines. The personnel and their respective potential vectors obtained from the streak flows are used to represent each frame as a graph. The frames of the surveillance videos are analyzed using graph theoretic approaches. The cumulative variation in all the frames is computed and a threshold based mechanism is used for classification and activity recognition. The experimental results discussed in the paper prove the efficiency and robustness of the proposed $\boldsymbol{GCBACS}$ for crowd behavior analysis and classification.

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## I. Introduction

Video surveillance systems fed by multiple high definition video streams have become a common feature in public and private spaces. The video surveillance systems are generally used to monitor activities and maintain vigil. The steady population growth observed in the past decade have resulted large crowd movements especially in public spaces like airports, train stations , bus stations, shopping malls, religious places, etc. The video surveillance feeds of such public spaces are currently monitored manually and are prone to human error. The number of crowd accidents observed have increased in the recent times [1].

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 [2] [3] [4] for some time now. The open research issues that exist and require attention with respect to crowd analysis can be listed as modelling or knowledge extraction from crowd patterns [5][6][7][8] and crowd behavior analysis [9] [10] [11]. 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 ($GCBACS$). 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.

To study the behavior of personnel in the crowd, tracking methodologies are generally used. The commonly used tracking methodologies [2] [3] [4] fail when large crowds are considered. To overcome this drawback, researchers proposed the consideration of fixed cell sizes to identify local trajectories and later map it together to obtain the personnel trajectory patterns [8] [10] [12]. The frames are split into uniform cells in these approaches. The use of optical flow techniques within each cell is considered to obtain the trajectory patterns of personnel within a cell. The optical flow techniques exhibited better results when compared to traditional tracking methodologies [13]. The drawback of the optical flow is that only two consecutive frames are considered to obtain personnel trajectory patterns. The optical flow method are not able to capture long term does temporal dependencies [14]. To overcome this drawback the concept of particle flow was introduced in [14]. The particle flow computation is achieved by displacing a grid of particles with optical flow through numerical integration techniques, providing trajectories that relate a particles original position to its position at a later time. The particle flow mechanisms proved to be computationally very heavy and minute personnel

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motion details were ignored. The introduction of streaklines flows to obtain the trajectories of personnel in the crowd proved to provide accurate analysis results [15]. For crowd behavior classification in [16] an unsupervised machine learning technique based framework was proposed. The framework in [16] considered hierarchical Bayesian models to connect the visual features, "atomic" activities and the interactions for classification. In [15] streaklines coupled with social force models were used to detect 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 drawback the $GCBACS$ 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 $GCBACS$ considers each frame as a graph with sub graphs. All the frames are analyzed and the cumulative variance is computed. If the $GCBACS$ observes that the cumulative variance is greater than a threshold the activity of the personnel in the crowd is classified as an abnormal activity.

The remaining manuscript is organized as follows. Section two discusses the literature review. The $GCBACS$ is discussed in section three of the paper. The experimental study conducted to evaluate the performance of the $GCBACS$ is discussed in the penultimate section of the paper. The conclusion and future work is discussed in last section of this paper.

## II. Literature Review

In this section of the paper a brief of the literature review conducted during the course of the research work presented here is discussed.

Hang Su et al. [17] propose a novel spatio-temporal viscous fluid field to recognize the large-scale crowd behavior from both the appearance and driven factor perspectives and present a spatio-temporal variation matrix to capture crowd motion characteristics and model the motion pattern as a spatio-temporal variation fluid field. They construct a codebook by clustering neighboring pixels with similar spatio-temporal features, and consequently, crowd behaviors are recognized using the latent Dirichlet allocation model. The drawbacks of this paper, when the interaction among pedestrian and estimate the interaction force between the pedestrians with sheering force in viscous fluid, which is referred to as spatiotemporal force field.

Si Wu et al. [18] proposed approach which is based on optical flow. For low quality videos, the resulting optical flow fields become unstable. To reduce the impact of noise, we use a regular grid to partition the flow field into a set of patches and focus on the average optical flow vector of each patch. The drawback of the proposed approach is limited by the accuracy of optical flow estimation.

BerkanSolmaz et al [19] proposed a framework to identify multiple crowd behaviors (bottlenecks, fountainheads, lanes, arches, and blocking) through stability analysis for dynamical systems, without the need for object detection, tracking, or training. The proposed method is deterministic and cannot capture the randomness inherent in the problem without a stochastic component.

Duan-Yu Chen et al. [20] proposed a real time constraint, each isolated region is considered a vertex and a human crowd is thus modeled by a graph. To regularly construct a graph, Delaunay triangulation is used to systematically connect vertices and therefore the problem of event detection of human crowds is formulated as measuring the topology variation of consecutive graphs in temporal order.

NuriaPelechano et al. [21] have shown a significant improvement in evacuation rates when using inter-agent communication. We can also observe the grouping behavior that emerges when there are a high percentage of dependent agents in the crowd. Only a relatively small percentage of trained leaders yield the best evacuation rates. We can visualize these results in real time with either our simple 2D or 3D viewer. Areas where there is room for improvement include adding individualism into Helbing's model so that agents would have different local motions depending on their roles.

## III. Graph Theoretic Approach Based Crowd Behavior Analysis and Classification System (GCBACS)

*a) System Modeling*

Let us consider 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 $\mathrm{J}^2$. 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 $m\,(t\colon t_{i,} m_i)$. At the initial instance i.e. $\dot{t} = 0$ the trajectory is represented as $m\,(t\colon t_{0,} m_0)$. The trajectories is utilized for optical flow $\bar{J}$ computations. From the optical flows the streak lines $\Lambda$ and path lines $K$ of the personnel in the crowd are computed frame wise. The streak flow $\Gamma$ 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 carried out on the similarity and deviations are observed. Cumulative variance $\overline{\mathbb{F}_{\mathbb{V}}}$ is computed considering all the previous frames and the current frame. If the variance is greater than the threshold $\varphi$ then abnormal activity is said to be detected. The $GCBACS$ proposed in this paper can be understood based on the model shown in Figure 1 of this paper.

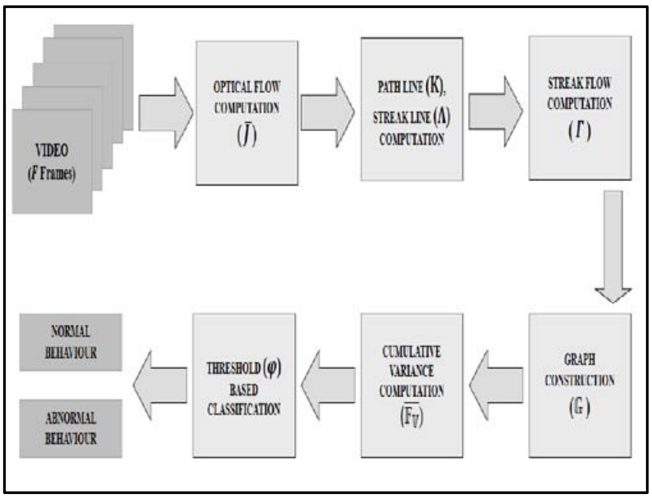


*Figure 1 :* GCBACS model overview

*b) Optical Flow Computation*

In $GCBACS$ 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 $\mathrm{I}$ be represented as $v\,(M,t)$. The velocity satisfy the continuity in time $C^0$ and continuity in space $C^2$ domain to obtain smooth optical flows. To achieve optical flow computation a hierarchical graph structure is considered to represent the video $F\ \times n$. Let the levels $L$ of the graph be defined as $L = 1,2,3 \ldots L_{max}$. If $e$ represents the velocity then the optical flow residual vector $e^{L-1}$ is used to minimizes the function vector $\varepsilon^{L-1}(e^{L-1})$. Similarly the matching function $\varepsilon^{L}$ can be minimized using the residual vector $e^{L}$. The primary guess for the $L^{th}$ level of the optical flow is denoted as $g^{L} = [g_a^L g_b^L]$. The value of $g^{L}$ is obtained by optical flow computations from $L_{max}$ to $L-1$. The frame $P$ and $Q$ can be represented on the basis of the optical flows computed at all the levels and is represented as

$$\forall(a,b)\,\epsilon\,([p_a-\omega_a-1, p_a+\omega_a+1] \times [p_b-\omega_b-1, p_b+\omega_b+1]), P(a,b) = U^L(a,b) \quad (1)$$

$$\forall(a,b)\epsilon([p_a-\omega_a, p_a+\omega_a] \times [p_b-\omega_b, p_b+\omega_b]), Q(a,b) = V^L(a+g_a^L, b+g_b^L) \quad (2)$$

Where $\omega_a, \omega_b$ are two integer values and $U$ and $V$ represent the previous two frames.

Based on the above equations it can be observed that there exist a domain definition difference between $Q(a,b)$ and $P(a,b)$. The optical flow representation of the frame $Q(a,b)$ is defined over the window size $(2\omega_a+3)\times(2\omega_b+3)$ instead of using $(2\omega_a+1)\times(2\omega_b+1)$. Consider that the displacement vector is $\bar{J} = [J_a \quad J_b]^T = e^L$ and image position vector is $N = [p_a \quad p_b]^T$. The vector $\bar{J}$ minimizes the matching function $\varepsilon(\bar{J})$. The function $\varepsilon(\bar{J})$ is defined as

$$\varepsilon(\bar{J}) = \varepsilon(J_a\ J_b) = \sum_{a=p_a-\omega_a}^{p_a+\omega_a} \sum_{b=p_b-\omega_b}^{p_b+\omega_b} ((P(a,b) - Q(a + J_a, b + J_b))^2) \quad (3)$$

An iterative Lucas –Kanade method is adopted to solve the function $\varepsilon(\bar{J})$ and is represented as

$$\frac{\partial\varepsilon(\bar{J})}{\partial\bar{J}} = -2\sum_{a=p_a-\omega_a}^{p_a+\omega_a} \sum_{b=p_b-\omega_b}^{p_b+\omega_b} (P(a,b) - Q(a+J_a, b+J_b)).\left[\frac{\partial R}{\partial s}\frac{\partial R}{\partial t}\right] \quad (4)$$

Using the first order first order expansion about the point $\bar{J} = [0\ 0]^T$ instead of $Q(a+J_a, b+J_b)$ Equation 4 can approximated as

$$\frac{\partial\varepsilon(\bar{J})}{\partial\bar{J}} \approx -2\sum_{a=p_a-\omega_a}^{p_a+\omega_a} \sum_{b=p_b-\omega_b}^{p_b+\omega_b} \left(P(a,b) - Q(a,b) - \left[\frac{\partial Q}{\partial a}\frac{\partial Q}{\partial b}\right]\bar{J}\right).\left[\frac{\partial R}{\partial s}\frac{\partial R}{\partial t}\right] \quad (5)$$

Note that $(P\,(a,b) - Q\,(a,b))$ is the temporal frame image derivative at the point $[a\ \ b]^T$. The point is defined as

$$[ab]^T : \forall(a,b)\epsilon[p_a-\omega_a, p_a+\omega_a] \times [p_b-\omega_b, p_b+\omega_b] \quad (6)$$

The derivative at $[a\ \ b]^T$ is defined as

$$\partial U(a,b) = P(a,b) - Q(a,b) \quad (7)$$

In Equation 5, $\left[\frac{\partial R}{\partial s}\frac{\partial R}{\partial t}\right]$ is the gradient vector and $\nabla U$ can be defined as

$$\nabla U = \begin{bmatrix} U_a \\ U_b \end{bmatrix} = \left[\frac{\partial Q}{\partial a}\frac{\partial Q}{\partial b}\right]^T \quad (8)$$

The derivatives $U_a$ and $U_b$ can be computed directly from the image $P(a,b)$ in the $(2\omega_a+1)\times(2\omega_b+1)$, which is a neighborhood of the point $N$ independently from the next image $Q(a,b)$. The derivative images satisfy the expression $\forall(a,b)\epsilon[p_a -$

$\omega_b, p_a + \omega_a] \times [p_b - \omega_b, p_b + \omega_b]$ and can be defined as

$$U_a(a,b) = \left(\frac{\partial P(a,b)}{\partial a}\right) = \left(\frac{P(a+1,b) - P(a-1,b)}{2}\right) \quad (9)$$

$$U_b(a,b) = \left(\frac{\partial P(a,b)}{\partial a}\right) = \left(\frac{Q(a,b+1) - Q(a,b-1)}{2}\right) \quad (10)$$

Based on $U_a(a,b)$ and $U_b(a,b)$ defined above the computation of $\frac{\partial \varepsilon(\bar{J})}{\partial \bar{J}}$ is given as

$$\frac{1}{2}\frac{\partial \varepsilon(\bar{J})}{\partial \bar{J}} \approx \sum_{a=p_a-\omega_a}^{p_a+\omega_a} \sum_{b=p_b-\omega_b}^{p_b+\omega_b} (\nabla U^T \bar{J} - \partial U)\nabla U^T \quad (11)$$

$$\frac{1}{2}\frac{\partial \varepsilon(\bar{J})}{\partial \bar{J}} \approx \sum_{a=p_a-\omega_a}^{p_a+\omega_a} \sum_{b=p_b-\omega_b}^{p_b+\omega_b} \left(\begin{bmatrix} U_a^2 & U_a U_b \\ U_a U_b & U_b^2 \end{bmatrix}\bar{J} - \begin{bmatrix} \partial U & U_a \\ \partial U & U_b \end{bmatrix}\right) \quad (12)$$

Equation 12 can be further simplified and defined as

$$\frac{1}{2}\left[\frac{\partial \varepsilon(\bar{J})}{\partial \bar{J}}\right]^T \approx K\bar{J} - \bar{\iota} \quad (13)$$

Where

$$K = \sum_{a=p_a-\omega_a}^{p_a+\omega_a} \sum_{t=p_b-\omega_b}^{p_b+\omega_b} \begin{bmatrix} U_a^2 & U_a U_b \\ U_a U_b & U_b^2 \end{bmatrix}$$

$$\bar{\iota} = \sum_{a=p_a-\omega_a}^{p_a+\omega_a} \sum_{b=p_b-\omega_b}^{p_b+\omega_b} \begin{bmatrix} \partial U & U_a \\ \partial U & U_b \end{bmatrix}$$

As $\left.\frac{\partial \varepsilon(J)}{\partial J}\right|_{J=J_{opt}} = [0,0]$

and matrix $K$ is invertible, then the optical flow vector $\bar{J}_{opt}$ is defined as

$$\bar{J}_{opt} = K^{-1}\bar{\iota} \quad (14)$$

Considering $\bar{J}_{opt}$, it is evident that $P(a,b)$ contains information of the gradients in the $a$ and $b$ direction of $N$. A large number of iterations have to be considered to obtain accurate optical flow of personnel in the crowd video frames. 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 $\forall (a,b) \in [p_a - \omega_a, p_a + \omega_a] \times [p_b - \omega_b, p_b + \omega_b]$ then

$$Q_{\mathcal{W}}(a,b) = Q(a + J_a^{\mathcal{W}-1}, b + J_b^{\mathcal{W}-1}) \quad (15)$$

Using the optical flow methodology in $GCBACS$ the residual pixel trajectory vector and mismatch vectors are obtained. The residual vector $\mathcal{R}^{\mathcal{W}} = [\mathcal{R}_a^{\mathcal{W}} \mathcal{R}_b^{\mathcal{W}}]$ minimizes the error function $\varepsilon^{\mathcal{W}}(\bar{\mathcal{R}}^{\mathcal{W}})$, defined as

$$\varepsilon^{\mathcal{W}}(\bar{\mathcal{R}}^{\mathcal{W}}) = \varepsilon(\mathcal{R}_a^{\mathcal{W}} \mathcal{R}_b^{\mathcal{W}}) = \sum_{a=p_a-\omega_a}^{p_a+\omega_a} \sum_{b=p_b-\omega_b}^{p_b+\omega_b} \left((P(a,b) - Q_{\mathcal{W}}(a + \mathcal{R}_a^{\mathcal{W}}, b + \mathcal{R}_b^{\mathcal{W}}))^2\right) \quad (16)$$

Using Equation 14 the solution of $\varepsilon^{\mathcal{W}}(\bar{\mathcal{R}}^{\mathcal{W}})$ can be obtained and is given as

$$\bar{\mathcal{R}}^{\mathcal{W}} = K^{-1}\overline{\iota_{\mathcal{W}}} \quad (17)$$

Where the mismatch vector matrix $\overline{\iota_{\mathcal{W}}}$ is given as

$$\overline{\iota_{\mathcal{W}}} = \sum_{a=p_a-\omega_a}^{p_a+\omega_a} \sum_{b=p_b-\omega_b}^{p_b+\omega_b} \begin{bmatrix} \partial U_{\mathcal{W}}(a,b) & U_a(a,b) \\ \partial U_{\mathcal{W}}(a,b) & U_b(a,b) \end{bmatrix} \quad (18)$$

In Equation 16 $\partial U_{\mathcal{W}}$ represents the $\mathcal{W}^{th}$ frame difference and is defined as

$$\partial U_{\mathcal{W}}(a,b) = P(a,b) - Q_{\mathcal{W}}(a,b) \quad (19)$$

From Equation 18, we can observe that the spatial derivatives $U_a$ and $U_b$ are computed only once initially and $K$ is constant for an entire iteration loop. The parameter vector $\overline{\iota_{\mathcal{W}}}$ is iteratively computed at $\mathcal{W}$ steps. That vector $\overline{\iota_{\mathcal{W}}}$ is the amount of residual difference between the video frames after translation by the vector $\bar{J}^{\mathcal{W}-1}$. Based on the matrix $K$ and $\overline{\iota_{\mathcal{W}}}$, $\bar{\mathcal{R}}^{\mathcal{W}}$ is computed. The new pixel displacement is $\bar{J}^{\mathcal{W}}$ that is computed in the step $\mathcal{W}+1$ and is defined as

$$\bar{J}^{\mathcal{W}} = \bar{J}^{\mathcal{W}-1} + \bar{\mathcal{R}}^{\mathcal{W}} \quad (20)$$

The iteration steps to achieve convergence are repeated till the value of $\bar{\mathcal{R}}^{\mathcal{W}}$ is below a preset threshold or the $\mathcal{W}$ number of maximum iterations are completed. If $\mathcal{S}$ represents the number of iterations required to reach convergence then the optical flow vector can be defined as

$$\bar{J} = e^L = \bar{J}^{\mathcal{W}} = \sum_{\mathcal{W}=1}^{\mathcal{S}} \bar{\mathcal{R}}^{\mathcal{W}} \quad (21)$$

The optical flow based on the velocities in the $a$ and $b$ direction at the $t^{th}$ time instance can be represented as

$$\bar{J} = [J_a \quad J_b]^T \quad (22)$$

*c) Streakline Flow Computation*

The optical flow computed present gaps in the trajectories of personnel in the crowd. In $GCBACS$ the gaps in the optical flow of similar motion vectors are filled using the streak lines [15] and new trajectory vectors are established prior to analysis using graph theoretic approaches.

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

$$a_F^N(t+1) = a_F^N(t) + J_a(a_F^N(t), b_F^N(t), t) \tag{23}$$

$$b_F^N(t+1) = b_F^N(t) + J_b(a_F^N(t), b_F^N(t), t) \tag{24}$$

Where $J_a, J_b$ are obtained from the optical flow vectors. For all the frames $F$ and time $t = 1,2,3 \dots T$ using particle advection we can obtain a vector matrix. The columns of the matrix can be used to obtain the particle trajectory details from time $t$ to the current time $T$ and are called path lines. In this paper $\mathrm{K}^N(t,T)$ is used to represent the path lines. The row of the matrix can be used to obtain the streaklines that connect the particles from $t$ video frames that originated from the position $N$. The streaklines is represented using $\Lambda^N(0,t)$ notation in this paper. Inconstancies are noticed in the streak lines obtained. To overcome this drawback in [15] the extended particle was introduced based on the position $N$ and the optical flow velocities. The $l^{th}$ extended particle can be defined as

$$\mathrm{E}_l = \left\{a_l^N(t), b_l^N(t), J_a^l, J_b^l\right\} \tag{25}$$

Where $J_a^l = J_a(a_l^N(l), b_l^N(l), l)$ and $J_b^l = J_b(a_l^N(l), b_l^N(l), l)$.

Based on the streak lines the behavior of the personnel in obtained. Using the streak lines, the streak flow is computed and is defined as

$$\Gamma_s = (J_a^s, J_b^s)^T \tag{26}$$

The streak line computation is realized by integrating the optical flows $\bar{J}$ computed and forming extended particles. To compute $\Gamma_s$, $J_a^s$ and $J_b^s$ have to be computed. The computation of $J_a^s$ and $J_b^s$ are similar in nature. If $J_a^l \in \mathrm{E}_l \forall_{l,\mathrm{E}}$ then let us consider a vector $\mathcal{J}_a = [J_a^l]$ to obtain the streak flow in the $a$ direction. The extended particle $\mathrm{E}_l$ 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

$$J_a^l = a_1 J_a^s(i_1) + a_2 J_a^s(i_2) + a_3 J_a^s(i_3) \tag{27}$$

In Equation 26 $i_{indx}$ represents the index of the pixel, $a_{fn}$ represents the basis function. 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 26 we can state

$$\mathfrak{L} J_a^s = J_a^l \tag{28}$$

Where $a_{fn}$ are the elements of the matrix $\mathfrak{L}$. Based on Equation 25 and 26 similarly $J_b^s$ can be computed. Using $J_a^s$ and $J_b^s$ the streak flow $\Gamma_s$ is obtained. In $GCBACS$ 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.

*d) Graph Therotic Mechanism For Analysis And Classification*

In $GCBACS$ the behavior of crowd personnel observed using the streak flow is analyzed using a graph structure adopted for all the $F$ frames of the video. Let us consider a graph $\mathbb{G}(\mathbb{V},\mathbb{E})$ obtained from the streak flow $\Gamma_F$. The vertices of the graph are the number of pixel vectors observed and is defined as

$$\mathbb{V} = \{v_1, v_2, \dots v_n\} \tag{29}$$

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

$$\mathbb{E} = \{e_1, e_2, \dots e_m\} \tag{30}$$

The streak flow $\Gamma$ computed represents a planar field, and $\Gamma = \Gamma_c + \Gamma_r$ based on the decomposition defined by Helmholtz. $\Gamma_c$ is the incompressible part and $\Gamma_r$ is the irrotational part of the vector field. In [22] two functions are introduced such that, $\Gamma_c = \Delta\alpha$ and $\Gamma_r = \Delta\beta$. The stream function $\alpha$ and the velocity potential function $\beta$ are computed using Fourier Transforms as described in [22]. The functions $\alpha$ and $\beta$ are defined as

$$\alpha(a,b) = \alpha_0 + \left(\frac{1}{2} \times \int_0^b \left(J_a^c(a,s) + J_a^c(0,s)\right) ds\right) - \left(\frac{1}{2} \times \int_0^a \left(J_b^c(s,b) + J_b^c(s,0)\right) ds\right) \tag{31}$$

$$\beta(a,b) = \beta_0 + \left(\frac{1}{2} \times \int_0^a \left(J_a^r(s,b) + J_a^r(s,0)\right) ds\right) + \left(\frac{1}{2} \times \int_0^b \left(J_b^r(a,s) + J_b^r(0,s)\right) ds\right) \tag{32}$$

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

$$\mathbb{E} = \{\alpha, \beta\} \tag{33}$$

To detect abnormal behavior analysis of consecutive frames is considered i.e. graph $\mathbb{G}_{t-1}$ and graph $\mathbb{G}_t$. The relation amongst the graphs can also be considered as the relation amongst the sub sets of $\mathbb{G}_{t-1}$ and $\mathbb{G}_t$ and is defined as

$$\mathcal{R}_{\mathbb{G}} = \left(\frac{\mathcal{R}}{Min(\mathbb{V}_{t-1}, \mathbb{V}_t)}\right) \tag{34}$$

Where $\mathcal{R}$ represents the number of vectors common to the graphs $\mathbb{G}_{t-1}(\mathbb{V},\mathbb{E})$ and $\mathbb{G}_t(\mathbb{V},\mathbb{E})$.

$$A_{\mathbb{G}}^N = \left(1 - \left(\frac{\mathcal{M}}{Max(\mathbb{G}_{t-1}^{Sub}, \mathbb{G}_t^{Sub})}\right)\right) \tag{35}$$

Where $\mathcal{M}$ is the number of matched sub graphs observed in the graph frames $\mathbb{G}_{t-1}(\mathbb{V},\mathbb{E})$ and $\mathbb{G}_t(\mathbb{V},\mathbb{E})$. $\mathbb{G}_{t-1}^{Sub}$ represents the sub sets of $\mathbb{G}_{t-1}$ and $\mathbb{G}_t^{Sub}$ represents the sub sets of $\mathbb{G}_t$. The matching of the energy potential functions of the frames is given by

$$\mathbb{P}_{\mathbb{G}} = \left(\frac{\sum_{x=1}^{m}\left|\frac{e_x^{t-1}-e_x^t}{e_x^{t-1}}\right|}{m}\right) \quad (36)$$

The local differences in the sub sets are measured to analyze the finer movements in the graphs and is computed using

$$\mathfrak{D} = \left(\frac{f(\mathbb{G}_{t-1}^{Sub},\mathbb{G}_t^{Sub})}{(f_{Max}-f_{Min})}\right) \quad (37)$$

Where $f(x)$ is a function that defines the matching between the sub sets $\mathbb{G}_{t-1}^{Sub}$ and $\mathbb{G}_t^{Sub}$. Combining all the above definitions the variance between two frames represented as graphs is measured as

$$\mathbb{F}_{\mathbb{V}} = \left((Max(1-\mathcal{R}_{\mathbb{G}}, A_{\mathbb{G}}^N)) \times (\gamma \times \mathbb{P}_{\mathbb{G}} + (1-\gamma)\mathfrak{D})\right) \quad (38)$$

Where $\gamma$ is a predefined integer. The cumulative variance observed till the $F^{th}$ frame can be defined as

$$\overline{\mathbb{F}_{\mathbb{V}}} = \sum_{x=1}^{F}\mathbb{F}_{\mathbb{V}} \quad (39)$$

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

$$\begin{cases} F_{Class} = 0, & If\ \overline{\mathbb{F}_{\mathbb{V}}} < \varphi \\ F_{Class} = 1, & If\ \overline{\mathbb{F}_{\mathbb{V}}} \geq \varphi \end{cases} \quad (40)$$

Having discussed the $GCBACS$ proposed in this paper, its performance is evaluated in the next section of this paper.

## IV. Performance Evaluation

To evaluate the performance of the $GCBACS$ the authors have considered the data set from University of Minnesota [23]. The dataset [23] consists of abnormal and normal crowd personnel videos. In this paper two scenarios are from the dataset are considered. They are referred as scenario 1 and scenario 2 in this section of the paper. The performance of the $GCBACS$ is compared with the Viscous Fluid Field ($VFF$) method proposed in [17]. Matlab is used to develop $GCBACS$. The performance presented here is based on the recognition results and the quantitative evaluations studied. In scenario 1 the outdoor crowd personnel activity is monitored. Indoor environments are characterized by lower lighting conditions and analyzing the personnel behavior can be achieved only if robust techniques are in place.

### *a) Recognition Results*

The recognition results obtained on evaluating the performance of the $GCBACS$ and $VFF$ 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 $GCBACS$ exhibits better accuracy when compared to the system proposed in [17] i.e. $VFF$. The $GCBACS$ nearly follows the ground truth bar shown in the figure. The misclassification ratio of the $GCBACS$ was found to be 0.05 and the miss classification ratio of $VFF$ was found to be 0.14. From the figure it is noticed that the $VFF$ has a few misclassified values which is also seen in the results shown in [17]. The misclassification is reduced as the $GCBACS$ 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 $GCBACS$ proposed in this paper can be efficiently adopted for crowd behavior study and analysis under varying conditions i.e. indoor and outside scenarios.

### *b) Quantitative Evaluations*

To evaluate $GCBACS$ and $VFF$ quantitatively, the red bars which represent abnormal activities detected are considered to be positive events. The results are evaluated using receiver operating characteristic curves ($ROC$) [24]. The $ROC$ curve obtained for scenario 1, scenario 2 is shown in Figure 3 and Figure 4. From Figure 4 and Figure 5 it is clear that the $GCBACS$ exhibits a better crowd activity classification when compared to the $VFF$ system. Considering Scenario 1 it is observed that the area under the $ROC$ curve for $GCBACS$ is 0.89 and 0.68 for the $VFF$. The area under the $ROC$ curve for $GCBACS$ and $VFF$ is 0.97 and 0.79, considering scenario 2. Both $GCBACS$ and $VFF$ 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 $ROC$ curve of $GCBACS$ is more than the area under the $ROC$ curve for $VFF$.

The accuracy and efficiency plots for scenario 1 are shown in Figure 5 and Figure 6 of the paper. From Figure 5 it is observed that average activity classification accuracy of $GCBACS$ is 0.83. The average activity classification accuracy considering the $VFF$ system is 0.71. In Figure 6 it is observed that the crowd activity classification efficiency of $GCBACS$ is 17.4% better than $VFF$. Considering scenario 2 the crowd activity classification accuracy and efficiency plots are shown in Figure 7 and Figure 8 of this paper. Considering Figure

7 it is observed that the average activity classification accuracy of $GCBACS$ is 0.88. The average activity classification accuracy of $VFF$ is 0.76. $GCBACS$ exhibited a 13.8% greater crowd activity classification efficiency than the $VFF$ system. The improvement in activity classification efficiency can be proved from Figure 8 of this paper.

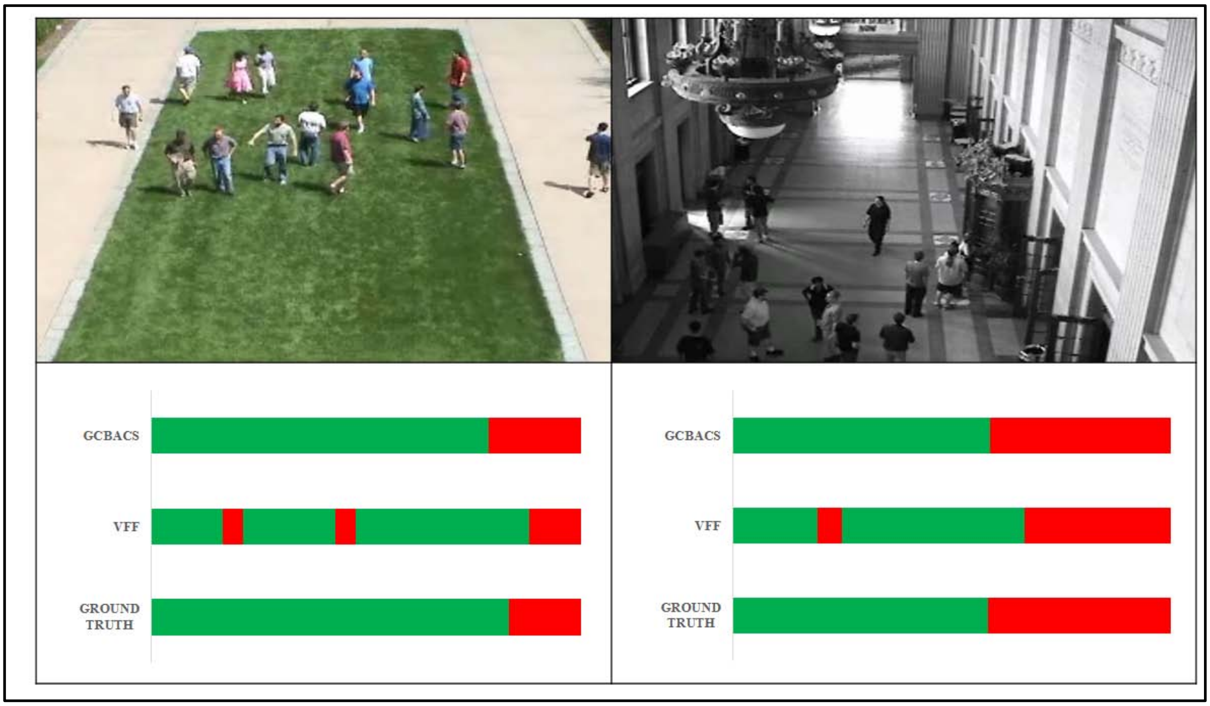


*Figure 1 :* Comparison results of crowd behavior recognition and classification for sample videos in Sequence 1 and Sequence 2 Using GCBACS and VFF. The ground Truth is also shown.

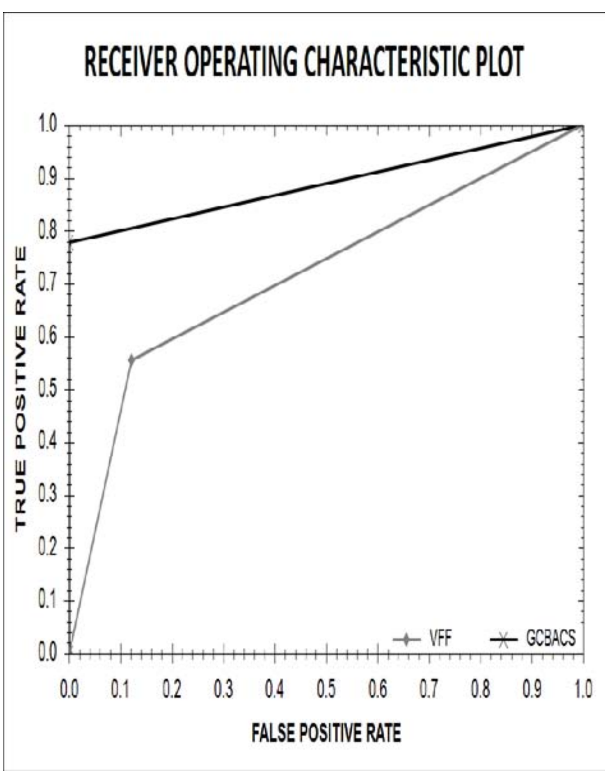


*Figure2 :* ROC Curves for Crowd Activity Classification based on GCBACS and VFF for Scenario 1

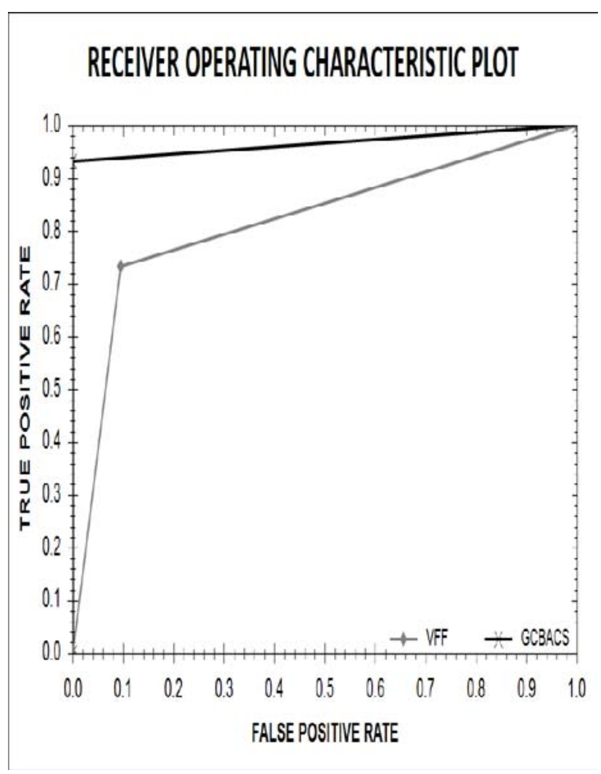


*Figure 3 :* ROC Curves for Crowd Activity Classification based on GCBACS and VFF for Scenario 2

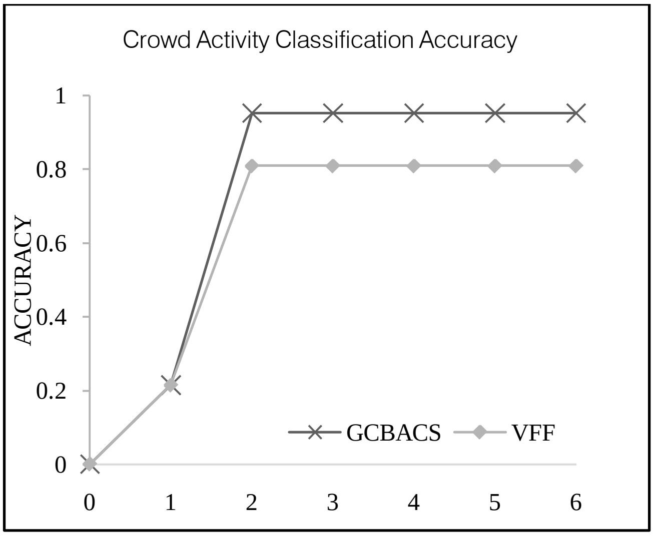


*Figure 4 :* Crowd Activity Classification Accuracy based on GCBACS and VFF for Scenario 1

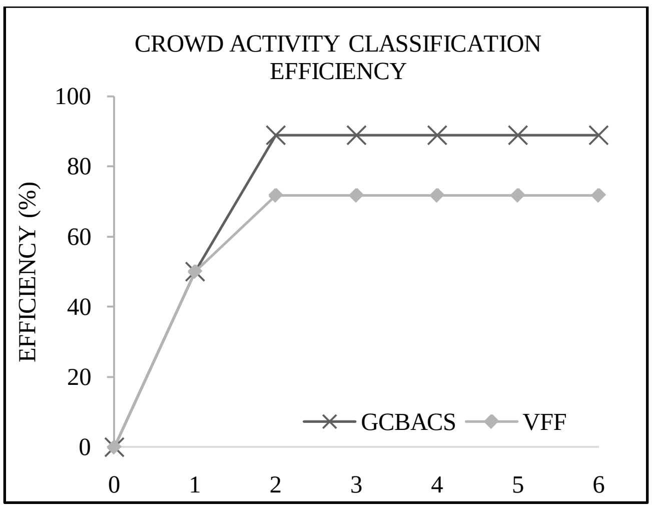


*Figure 5 :* Crowd Activity Classification Efficiency based on GCBACS and VFF for Scenario 1

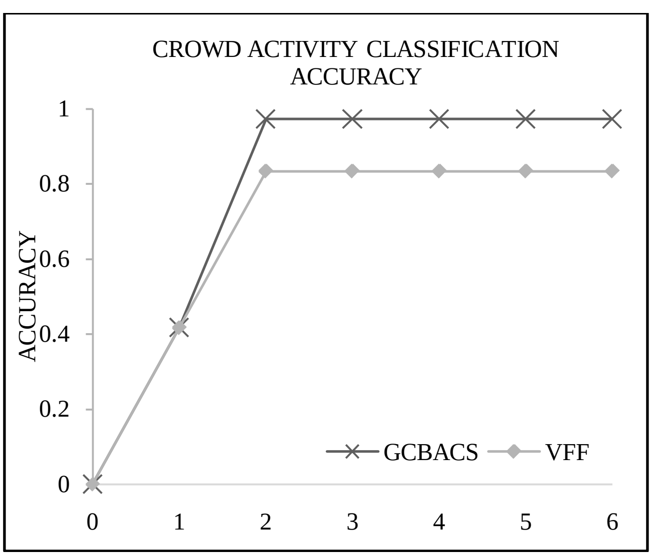


*Figure 6 :* Crowd Activity Classification Accuracy based on GCBACS and VFF for Scenario 2

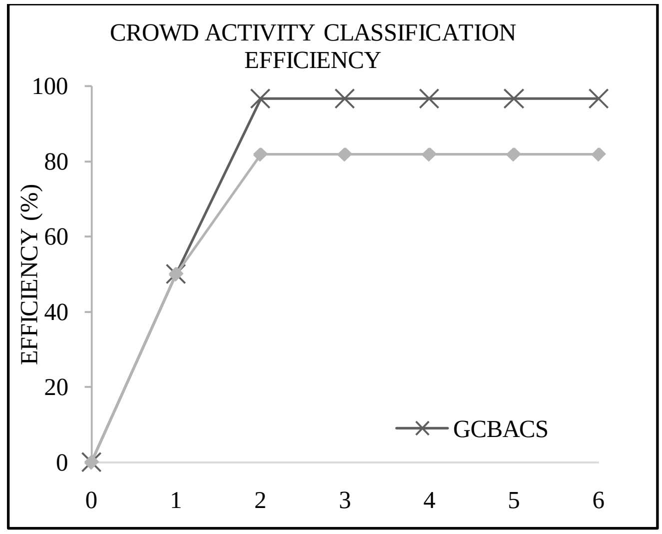


*Figure 7 :* Crowd Activity Classification Efficiency based on GCBACS and VFF for Scenario 2

The results presented in this paper prove that the proposed $GCBACS$ out performs the $VFF$ algorithm proposed in [17] in terms of the classification accuracy, classification efficiency and the area under the $ROC$ curve.

## V. Conclusion and Future Work

This paper introduces the $GCBACS$ for surveillance video crowd behavior and analysis. The $GCBACS$ 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 $GCBACS$ can be utilized for analysis of indoor and outdoor crowd surveillance videos. The results validate that the proposed $GCBACS$ 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 $GCBACS$ in varied datasets.

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