International Journal of Recent Technology and Engineering (IJRTE)
ISSN: 2277-3878, Volume-7, Issue-6S, March 2019

Particle Filtering Based Opticle Flow Computation Model for Crowd Anomaly Detection Using Gaussian Mixture Model

Vijay A. Kotkar, V. Sucharita

Abstract---* Recently, real-time security applications have attracted researcher, industry and real-time application field due to their unmatched security provisioning tasks and improve the security aspects in private and public places. In this field of security, visual surveillance system plays important role which is generally performed with the help of video-clips and recordings. A surveillance system is considered an application scenario which can perform the early detection of abnormality and threat assessment to protect the human from crowd-related issues and ensure the public safety of humans. Computer vision based image processing applications are widely adopted in these applications where videos can be processed for feature extraction such as people, movement and flow from the video sequence. Several researches have been carried out in this field which is based on the feature extraction and classification process but achieving the desired performance for complex scenarios is still considered as a challenging task. Hence, in this article, we present computer vision based novel technique for crowd-behaviour analysis. the proposed approach is divided into multiple stages where according to the first stage, crowd model is developed using particle filtering scheme and later motion patterns are extracted using SFM (Social Force model) along with a novel clustering scheme which helps to identify the pixel information, later, optical flow and streak line flow computation model is developed, later interest point detection and tracking scheme is applied and distribution of crowd is identified which is later classified using GMM (Gaussians Mixture Model) based approach. The complete experimental study is carried out using MATLAB simulation tool and we present a comparative experimental study which shows that the proposed approach achieves better performance of crowd behaviour detection and classification.

I. INTRODUCTION

Recently, the demand of automated visual surveillance system has increased drastically in real-time monitoring systems and research applications. These types of applications are build up with the help of multiple research areas such as machine vision, signal processing, sensor information processing and pattern recognition. Due to increasing demand of security applications, human behaviour analysis became a crucial step for better security and surveillance systems. Detection of human activities in crowded scenes is a challenging task and it is considered as a very useful task for surveillance systems [1]. Currently, group behaviour analysis and detection has attracted researchers due to their impact on security applications and monitoring performance improvement for real-time and offline application. Moreover, group behaviour analysis and activity detection, escalate the other applications such as disturbance detection, riots and other activities from video sequences [2]. Hence, an automated system for crowd behaviour analysis is required which can be used for monitoring the public places. In this field of crowd behaviour analysis, abnormal crowd behaviour detection has gained lot of attraction from the research communities. Fig. 1 shows two samples for normal and abnormal crowd behaviour activity. The modeling of crowds is divided into two main approaches as: microscopic approach and macroscopic approach. According to the microscopic approach, crowd data is considered as a collection of multiple individual activities. Moreover, each individual is detected and tracked in these processes [3] for crowd behaviour detection. In general, these techniques are suitable for the small-scale crowd behaviour detection and classification but fails for the dense crowd scenario due to the complex structure and various types of occlusions. On other hand, macroscopic crowd behaviour analysis techniques are introduced where a large-scale dense crowd is considered as a single entity for analysis [4]. According to these techniques, pixels are considered as particles and feature modeling is applied on the particles for crowd behaviour analysis by applying object segmentation and tracking strategies. Zhan et al. [5] presented a review study and concluded that the group behaviour detection can be categorized into three main categories where two categories discussed before as microscopic, macroscopic and combined approach where both schemes i.e. individual analysis and entire video frames analysis are performed. Ali et al. [6] presented a novel strategy where individual tracking and complete video data are processed for anomaly detection.

An anomaly is defined as the deviation of something form it's actual or standard model. In video sequences also, this can be defined as the abnormal behaviour of individual from the normal behaviour. Hence, abnormal events or crowd behaviours can be identified by comparing the suspect events with the normal events. According to a study presented in [4], suggested that the conventional computer vision schemes may show degraded performance because of inappropriate feature representation for crowded scenes. According to a study presented in [4], various challenges present in this field such as recent capturing devices are costly to upgrade the devices for better capturing hence, the desired cameras only upgraded hence complete efficient monitoring not be provided due to poor quality videos.

Revised Manuscript Received on March 10, 2019.

Vijay A. Kotkar, Research Scholar, Department of Computer Science & Engineering, K L University, Vijayawada, Andhra Pradesh, India (vijaykotkar26@gmail.com)

Dr. V. Sucharita, Professor, Department of Computer Science & Engineering, Narayana Engineering College, Gudur, Andhra Pradesh, India (jesuchi78@yahoo.com)

Normal Activity Sample frame

Abnormal Activity sample frame

Fig.1. Sample images of normal and abnormal crowd activity

Moreover, these types of CCTV cameras suffer from the environmental conditions such as low-illumination and contrast resulting in poor information analysis from the captured videos. In addition to this, dense crowd environments face challenges due to occlusions and complexities due to the crowd movement. Due to this movement, visual consistency and shape of the objects and the occlusion positions also vary which causes poor descriptor generation. These captured have low spatial and temporal resolution which leads towards the poor quality feature representation.

In order to perform the abnormal crowd behaviour detection and classification in surveillance videos, two main factors need to be addressed which are known as representation of event and measurement of anomaly in the surveillance video. During last decade several techniques have been introduced where spatial-temporal information schemes have been used such as Adam et al. [7] introduced histogram of optical flow, Chun et al. [8] introduced histogram of motion direction, spatial-temporal framework based on HoG [9], social-force model for tracking [10], Luo et al. [11] introduced chaotic invariant model for action recognition, depth image based action recognition using Spatio-temporal features using HMM [12] and particle filtering [13]. On the other hand, classification of activity depends on the classifier's performance. Several classifiers have been used for distinguish the action and crowd behaviour efficiently. Singh et al. [14] used graph formulation process for representation of crowd and classified the abnormal behaviours using kernel based SVM, deep learning [15], Convolutional Neural Network (CNN) [16], Hidden markov Model [17] and fuzzy k-means [18] etc.

Significant amount of work has been presented in this field of abnormal crowd behaviour detection and still is considered as a hot research area because still several issues are present in the current researches which need to be addressed. Generally, these techniques of video analysis require object detection and tracking for behaviour detection process. However, crowded scenes suffer from the high occlusion, clutters and ambiguities in the video sequences where conventional methods fail to perform the desired task with prior knowledge and considerations about the video sequence. Moreover, crowd dynamics modeling is also considered as a complex task which plays an important role in the crowd behaviour analysis.

In this work, we address these issues for abnormal crowd behaviour detection and introduce a novel approach for detection of abnormal crowd behaviour.

The rest of the article is organized as follows: section presents recent techniques and methods presented for abnormal crowd behaviour detection, proposed approach and its modeling is presented in section III, section IV presents experimental & comparative analysis and finally, section V presents the concluding remarks about the proposed approach for abnormal crowd behaviour detection.

II. LITERATURE SURVEY

This section presents a brief discussion about recent techniques in the field of abnormal crowd behaviour detection. Several schemes have been developed for abnormal crowd behaviour detection in crowded scene analysis [19-21]. The existing techniques are mainly divided into two main categories a description based methods for crowd behaviour analysis and statistical based techniques for crowd behaviour detection. According to the description based methods, space and time structure behaviour are extracted and stored for further evaluation. In these processes, crowd behaviour is evaluated by dividing the sub-behaviour i.e. first of all, the complete event is divided into basic events, single-multi line events and then combined event based on the time structure. On other hand, statistical methods are considered as improved and promising solution for the crowd behaviour detection. These techniques are suitable to perform in the noisy and cluttered environment where less training data is present [22]. Sah et al. [23] presented a technique for abnormal human behaviour detection. According to this process, a semantic metadata model approach with the help of multimedia standards to extract and annotate the abnormal behaviours from the video sequences. This technique is based on the study where complete crowd model is considered for processing.

In this field, social force model is widely adopted for better performance. Ji et al. [24] presented a social force model where block-level computation model is presented. Moreover, this method also uses pixel-level computation approach where Gaussian mixture modeling is applied for anomaly detection and later block-level segmentation approach is applied to detect and localize the anomalies using social force model. Zhang et al. [25] discussed about

Published By:
Blue Eyes Intelligence Engineering
& Sciences Publication

novel social attribute-aware force model for abnormal crowd behaviour detection. In this process, first of all scenes are scaled in an unsupervised process then later social information such as social disorder and congestion attribute are used for interacting the social behaviours. With the help of this, crowd interaction model is formulated where by using social force model, fused by online fusion technique. Finally, abnormal events are detected with the help of Social Attribute-aware Force Model (SAFM). Similarly, Feng et al. [26] focused on abnormal crowd behaviour analysis scheme using Probability Hypothesis Density (PHD) filtering scheme with Markov Chain Monte Carlo (MCMC) implementation. This technique uses social force model which helps to describe the interaction between targets where likelihood is computed during the PHD filter and later One Class Support Vector Machine (OCSVM) classifier is developed for activity recognition. Wen et. al. [27] also presented social force model based strategy combined with the violent flows descriptor for abnormal activity detection. According to this approach, SFM and Violent flows descriptors (VIF) are used for analyzing the stability status of the crowd. Later, Latent Dirichlet Allocation (LDA) model is developed using bag-of-words model where temporal and spatial features are computed and maximum likelihood estimation is applied to identify the abnormal events.

In this field, optical flow computation and streak line method based approaches have been adopted widely. Rojas et al. [28] also presented optical flow based computation where background subtraction approach is implemented and pattern learning is performed by using Gaussian Mixture Model (GMM). Direkoglu et al. [29] also introduced optical flow based method for abnormal crowd behaviour in this approach, optical flow vectors are enhanced by computing the angle difference between current and previous frame at corresponding pixel locations. The obtained angle difference is combined is used for generating the direction invariant effective features. Later, one-class SVM is utilized for classification of activities.

Several promising techniques have been developed to improvise the performance of abnormal crowd behaviour detection. Wu et al. [33] discussed about the escape incident from the scenarios where any abnormality occurs in the place. This can be identified using video surveillance techniques. Hence, authors presented a video processing technique for crowd abnormal behaviour detection using Bayesian framework. In order to present this approach, an initial model is created where crowd modeling is performed in the presence and absence of the anomalous events. This work generally focusses on the probability density function creation using optical flow computation modeling and later Bayesian model based escape detection and classification performed. However, this technique fails to achieve the desired performance due to the complex crowd scenarios and false alarm probability. Chen et al. [34] presented a study on human crowd behaviour analysis for better video surveillance and security applications. Generally, crowd nature is complex and follows a non-rigid shape which raises complexity for computer vision based applications. This issue can be addressed using optical flow modeling where adjacency-matrix based clustering scheme is applied to perform the clustering in unsupervised process. This clustering of human crowd is obtained by using crowd behaviour attribute, position, orientation and crowd size using a force field model.

III. PROPOSED MODEL

This section deals with the proposed approach of abnormal crowd behaviour detection using robust feature extraction and crowd representation modeling using computer vision techniques. The complete proposed approach is divided not the following phases: Adaptive particle advection using particle swarm optimization –social force model, Optical flow and streak line flow computation, Interest point detection and tracking using energy modeling and GMM based activity classification.

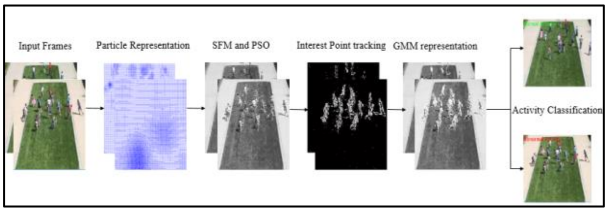


Fig. 2. Overall system architecture

Fig. 2 shows a complete process of proposed approach for crowd abnormal behaviour detection. The complete approach consists of four main stages as discussed before. According to the proposed approach, first of all, we apply adaptive particle advection process using PSO-SFM approach which helps to obtain the crowd information in the current frame, later optical- streak line flow is applied to estimate the complete motion flow model followed by the interest point tracking using energy modeling and finally, GMM (Gaussian Mixture Modeling) is applied for activity classification.

A. Adaptive particle advection modeling

In this sub-section, we present proposed adaptive particle advection modeling. According to the conventional schemes of particle advection, make use of rectangular window based approach where each frame is processed through the grid and during this phase, fourth-order Runge-Kutta approach is implemented which helps to compute the velocity of each particle. However, the main drawback of these approaches that it assumes that the complete crowd follows fluid dynamical model which limits the modeling of huge crowd and high complex scenarios. Moreover, unpredicted motion movement and trajectories also generate the unstructured flow of the crowd which is also a challenging task for crowd behaviour detection. Moreover, pixel information varies at each coordinate hence continuous social information is required which can’t be obtained by rectangular window. To overcome these issue, we present adaptive approach of particle advection using PSO for crowd behaviour modeling where Particle swarm optimization and social force modeling is applied which is later grouped with the help of clustering approach.

Published By:
Blue Eyes Intelligence Engineering
& Sciences Publication

Here, we present a brief discussion about PSO and SFM model used in this work. Later, a clustering model is developed which helps to identify the particle information and a new social force model is developed. Finally, we present a novel fitness function for optical flow computation.

B. Particle Swarm Optimization:

It is an iterative and population-generation based optimization process for finding the optimal solution for given problem in the considered search space. The main objective of this approach is providing the optimal solution for the performance criteria known as fitness function$f$. According to the general working process of PSO, an initial population is generated which is known as swarm where total N dimensional particles are distributed in the search space randomly. Each particle is considered as a point where optimization process makes use of particle points to achieve the optimal solution. In other words, each particle is updated at each iteration with the best value of the current particle $pbest_i$ which depends on the i^{th} particle whereas $gbest$represents the overall best value for warm population. These values are obtained by computing the fitness function as $f(pbest_i)$. However, the position of these particles changes at every iteration, hence the rate of change (v) called as velocity which can be given as:

$$\begin{gathered} v_i^{new} = W.v_i^{old} + C_1.rand_1. \\ \left(pbest_i - x_i^{old}\right) + C_2.rand_2. \\ \left(gbest - x_i^{old}\right) \\ x_i^{new} = x_i^{old} + v_i^{new} \end{gathered} \tag{1}$$

Where W denotes the inertia weight which require manual tuning for better global and local performance which helps to find the optimal solutions in fewer iterations, C_1 and C_2 are the scalar constants which are used for finding the global and local best values i.e. $pbest_i$ and $gbest$. Higher values of scalar constants create the gap between particles and target regions whereas lower values help to bridge the gap between targets and particles.$rand_1$ and $rand_2$ are the two random values in the range between 0 and 1., x_i^{old} is the old location of particles,x_i^{new} denotes the new location. Similarly, v_i^{old} denotes old velocity and v_i^{new} is the new velocity.

C. Social Force Model:

This section provides the discussion about social force model for crowd scenes by considering crowd model as individual particles. According to this process, each individual is denoted by i and carries a force as $\mathcal{F}_i$ which denotes the activity of individual in a particular manner. This force is known as social force and can be expressed as:

$$m_i \frac{d\mathcal{V}_i}{dt} = \mathcal{F}_i = \mathcal{F}_{int} + \mathcal{F}_d \tag{2}$$

Where m_i denotes the mass value for individual, actual velocity of individual is given by $\mathcal{V}_i$, desired moment force is given by $\mathcal{F}_d$and $\mathcal{F}_{int}$ denotes interaction force.

Desired movement force is a measurement representation of individual particle's desire to travel towards the destination. For this consideration, an assumption is made that the particle or individual is unrestricted and free to move towards the target with an initial desired speed. This force is velocity dependent force which can be expressed as:

$$\mathcal{F}_d = \frac{1}{\mathcal{T}}\left(\mathcal{V}_i^d - \mathcal{V}_i\right) \tag{3}$$

$\mathcal{V}_i^d$ denotes the desired velocity and $\mathcal{T}$ denotes the relaxation time which scales the required force of particle to move towards the target due to the obstacles which slowdowns the speed of individual. Due to the surrounding environment effects, desired movement force $\left(\mathcal{V}_i^d\right)$ can be re-written as:

$$\mathcal{V}_i^p = \mathcal{V}_i^d(1-\rho_i) + \langle \mathcal{V}_i^{avg} \rangle \rho_i \tag{4}$$

ρ_i weight threshold parameter and $\mathcal{V}_i^{avg}$ denotes the average velocity. With the help of these assumptions, the interaction force of SFM can be given as:

$$\mathcal{F}_{int} = m_i \frac{d\mathcal{V}_i}{dt} - \left(\mathcal{V}_i^p - \mathcal{V}_i\right) \tag{5}$$

In this work, we aim focus on the improve the interaction force model; we apply clustering method where motion coherence and spatial proximity parameters are extracted with the help of moving particles in a given video frame. In this process, we extract the periodic motion of an individual along with the vertical axis of the frame as gait feature extraction. In order to perform this, first of all, linear regression is applied to standardize the gait features as the center of frame and then periodic components$\left(y_p\right)$ are extracted based on these trajectories.

Let us consider that i^{th} component of periodic component y_p is dented by the $\mathcal{Y}_i$ and total number of components are given as N Fast Fourier Transform. Here we apply fast Fourier transform computation to obtain the phase and amplitude information, can be given as:

$$\mathcal{Y}_i = \sum_{k=0}^{N-1} \mathcal{Y}_k e^{-\frac{2\pi i k}{N}}, i = 0,1,2, \ldots .N-1 \tag{6}$$

In the next stage of clustering, first of all we construct graph in each time window where each node represents a separate trajectory, edges are connected to the identical minks obtained by Delaunay triangulation. The connectivity between two corresponding node i and $j$where weights of each link is represented based on the three metrics as spatial proximity, gait feature and motion difference [30-31]. With the help of these weights, total weights can be computed by multiplying the edge weights, as follows:

$$e_{i,j} = e_{i,j}^p e_{i,j}^g e_{i,j}^m \tag{7}$$

Where $e_{i,j}^p$ denotes the proximity features, $e_{i,j}^g$ denotes the gait feautre and $e_{i,j}^m$ gives the motion differnece. This grapah is furhter used for dividing into different clusters.

A. Interaction for computation:

As discussed before, $\mathcal{F}_d$ denotes the individual's desire to travel towards the destination node. However, the individual action can be affected due to surrounding $\mathcal{V}_i^d$ gives the maximum desired speed and $\langle\mathcal{V}_i^{avg}\rangle$ denotes the average speed which considers the particle group information and distance etc., and computed as:

$$\langle\mathcal{V}_i^{avg}\rangle = \frac{1}{K}\sum_{j=0}^{K-1}\mathcal{V}_j f_{ij}(t) \quad (8)$$

Where K denotes the total number of available particles moving in surrounding, t denotes the time period for i^{th} particle, $\mathcal{V}_j$ denotes the optical flow of the current particle j in (x_j, y_j) coordinates and f_{ij} denotes the influence factor computed from j to i. With the help of these parameters, the influence factor can be given as:

$$f_{ij}(t) = w_{ij}^p w_{ij}^d w_{ij}^\varphi \quad (9)$$

Where, $w_{ij}^d = -e\left(\frac{d_{ij}^2}{2r_d^2}\right)$, $w_{ij}^\varphi = \begin{cases}-1, \varphi_{ij} < \varphi_{viewangle} \\ 0, \ otherwise\end{cases}$ and $w_{ij}^\varphi = \begin{cases}0, \ i,j \in same\ group \\ 1, \ otherwise\end{cases}$.

In these assumptions, r_d denotes the influence radius relates the impact of two individuals as more impact if the radius is less, $\varphi_{viewangle}$ shows the effect of the capturing angle. Here, we assume that each type of crowd has some certain type and similar size objects hence the mass is considered similar and identical for all individuals. Hence, the interaction force can be re-written as:

$$\mathcal{F}_{int} = (\mathcal{V}_i^p - \mathcal{V}_i)\frac{1}{\mathcal{T}} - \frac{d\mathcal{V}_i}{dt} \quad (10)$$

According to the proposed approach, a video sequence is given as input where random particles are initialized in the first frame. During this process, initial guess of best fit for individual particle and global population are assigned as p_{besti} and g_{best} respectively. Here, particles are denoted by the corresponding 2D pixel values in the current frame. Since, it is an iterative process hence the values of best fit are updated if the new value is better than the old value. This measurement of best fit is carried out using fitness function computation on the social interaction force. Finally, the value of $gbest$ is updated after achieving the desired fitness in given number of iterations. The final particle position is considered as initial guess to the next frame and this process is repeated until the end of video sequence.

The fitness function is used for identifying the best model for interaction force for each movement of crowd scenario. Here, particles are evaluated by computing the interaction force computation using social force and optical flow model. Optical flow computation has the great ability to model the crowd velocities into the SFM. In this work, our main aim is to develop a joint model where optical flow and SFM can be used together hence optical flow density is defined which is computed for the i^{th} particle as:

$$\mathcal{S}_i = OF_{avg}(x_i^{new}) \quad (11)$$

Where $OF_{avg}(x_i^{new})$denotes the average value of optical flow for the ne coordinate location x_i^{new}, later, the desired velocity of particle $\mathcal{S}_i^p$ is given as $\mathcal{S}_i^p = OF(x_i^{new})$ which gives the intensity value of the particle i whose coordinates are obtained from the PSO initialization. With the help of these parameters, we compute the interaction model which is given as:

$$\mathcal{F}_{int}(x_i^{new}) = \frac{d\mathcal{S}_i}{dt}.m_i - (\mathcal{S}_i^p - \mathcal{S}_i)\frac{m_i}{\mathcal{T}_i} \quad (12)$$

Where velocity derivative component is identified by taking the difference between frames at t and $(t-1)$ i.e. it can be expressed as $\frac{d\mathcal{S}_i}{dt} = [OF(x_i^{new})|_t - OF(x_i^{new})|_{t-1}]$. According to this assumption, less interaction force will provide more information about the crowd flow and helps to model the crowd activity. Hence, the new fitness function can be written as:

$$Fitness = \min_i\{\mathcal{F}_{int}(x_i^{new})\} \quad (13)$$

B. Streakline Flow Computation

In this work, we have considered particle filtering based scheme for computation. In order to detect the crowd behaviour crowd flow analysis is considered as one of the important task which can be performed using well-known streakline flow method where pixels are considered as particles. This can help to identify the path of movement of individual particle. Let us consider that initial particle position is $\left(m_i^p(t), n_i^p(t)\right)$ given at time t which is initiated at the p point and i^{th} frame. The initial particle positions are described as:

$$\begin{aligned} m_i^p(t+1) &= m_i^p(t) \\ &\quad + u\left(m_i^p(t), n_i^p(t), t\right) \\ n_i^p(t+1) &= n_i^p(t) \\ &\quad + v\left(m_i^p(t), n_i^p(t), t\right) \end{aligned} \quad (14)$$

Where u and v denotes the optical field which gives the set of information of all particles at point P. Below given Fig. 3 shows a general representation of optical flow computation model applied in this work.

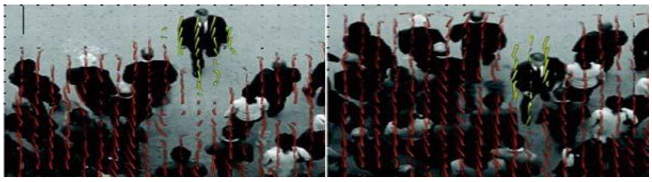


Fig. 3. Optical flow computation

To accomplish the visualization process, streakline for each particle is represented in colored material which also propagates along with the path. Similarly, streakline make use of optical flow $OF = (u, v)^T$ to propagate with the initial velocities. Based on this assumption, extended particles can be rewritten with the help of velocity parameters as:

$$P_i = \{m_i(t), n_i(t), u_i, v_i\} \quad (15)$$

Published By:
Blue Eyes Intelligence Engineering
& Sciences Publication

Where $u_i = u\left(m_i^p(i), n_i^p(i), i\right)$ and $v_i = v\left(m_i^p(i), n_i^p(i), i\right)$.

In order to represent the motion filed, a new streak-flow model is constructed based on the streaklines as $(\mathbb{F}_s = (u_s, v_s)^T)$. This can provide the complete motion information while flow is changing dynamically. In this, u and v are computed as $U = [u_i]$and $V = [v_i]$ respectively where $u_i \in P_i, \forall_{i,p}$ and $v_i \in P_i, \forall_{i,p}$, where streak flow is computed in both x and y direction. Moreover, it is also considered that each particle has three neighboring pixels, linear interpolation is applied and hence the updated u and v flows can be written as:

$$\begin{aligned} u_i &= \mathcal{J}_1 u_s(\mathcal{P}_1) + \mathcal{J}_2 u_s(\mathcal{P}_2) + \mathcal{J}_3 u_s(\mathcal{P}_3) \\ v_i &= \mathcal{J}_1 v_s(\mathcal{P}_1) + \mathcal{J}_2 v_s(\mathcal{P}_2) + \mathcal{J}_3 v_s(\mathcal{P}_3) \end{aligned} \quad (16)$$

where $\mathcal{J}$ denotes pixel index and $\mathcal{P}$is a triangulation function for neighbouring pixel. With the help of eq. (16) we option the complete flow model for the given frame. This process is also repeated until the end of video sequence.

C. Interest point tracking

In section 3.1.3, influence factor modeling is presented which also can be used for energy potential for interest points obtained from the optical flow. Potential energy value is high if the neighboring points are high and lower values are obtained if the objects are far from each-other. In this case, we have multiple subject scenarios; hence the influence of all subjects can be expressed in the term of potential energy for the subject p_i as:

$$\mathcal{E}_i = \frac{1}{N} \sum_{k \neq i, \mathcal{E}_{ik} > 0} \mathcal{E}_{ik} \quad (17)$$

N denotes the non-zero neighbouring points and this potential energy model $(\mathcal{E}_i)$helps to model the current behaviour state of individual subject.

D. GMM based classification

In this section we present GMM (Gaussian Mixture Model) based abnormal activity classification. First of all, we obtain the Gaussian distribution for the given data D at time t which can be given as:

$$P(D_t) = \sum_{i=1}^{\mathcal{G}} \eta\left(D_t, \mu_{i,t}, \psi_{i,t}\right) \delta_{i.t} \quad (18)$$

Where $\mathcal{G}$ denotes the total number of distributions, $\mu_{i,t}$ denotes the mean, $\psi_{i,t}$ denotes the covariance and $\delta_{i.t}$ denotes the weights of i^{th} Gaussian distribution at time t and η denotes the probability density function of the i^{th} Gaussian distribution as $\eta(D_t, \mu, \psi) = \frac{1}{(2\pi)^{\frac{n}{2}} |\psi|^{\frac{1}{2}}} e^{\frac{1}{2}(D_t - \mu_t)\psi^{-1}(D_t - \mu_t)^T}$.

In this process, weights are updated as follows:

$$\delta_{k,t} = \alpha M_{k,t} + (1 - \alpha)\delta_{k,t-1} \quad (19)$$

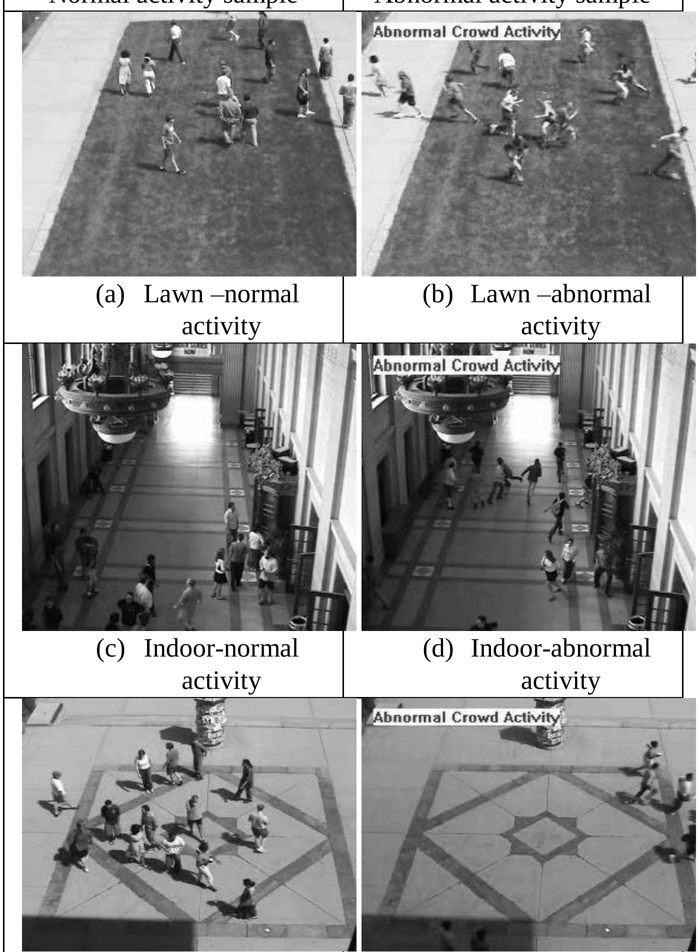
Where α denotes the learning rate used in K means approximation. Later, we focus on the identifying the correspondence of these variables in the normal distribution. This model gives us a mixture of total Z distribution which consists large weight and can be obtained as:

$$Z = argmin_z \left(\sum_{k=1}^{z} \psi_k > T \right) \quad (20)$$

Where T denotes the threshold value which helps to determine that where current pixel belongs to the background or image foreground. Based on these assumptions of distribution, we found Z total distribution which can be defined as recognized activity based on the threshold value. If the value of threshold is more, then less chance are present for abnormal event otherwise lower value of threshold will be considered as abnormal event indication.

IV. RESULTS AND DISCUSSION

This section presents complete experimental and comparative analysis. The proposed approach is implemented using MATLAB tool running on windows platform and the computer is configured with Intel i3 processor with 4GB RAM. In order to perform this task, we have considered UMN dataset [32]. Some sample images of normal and abnormal event are depicted in Fig. 4.

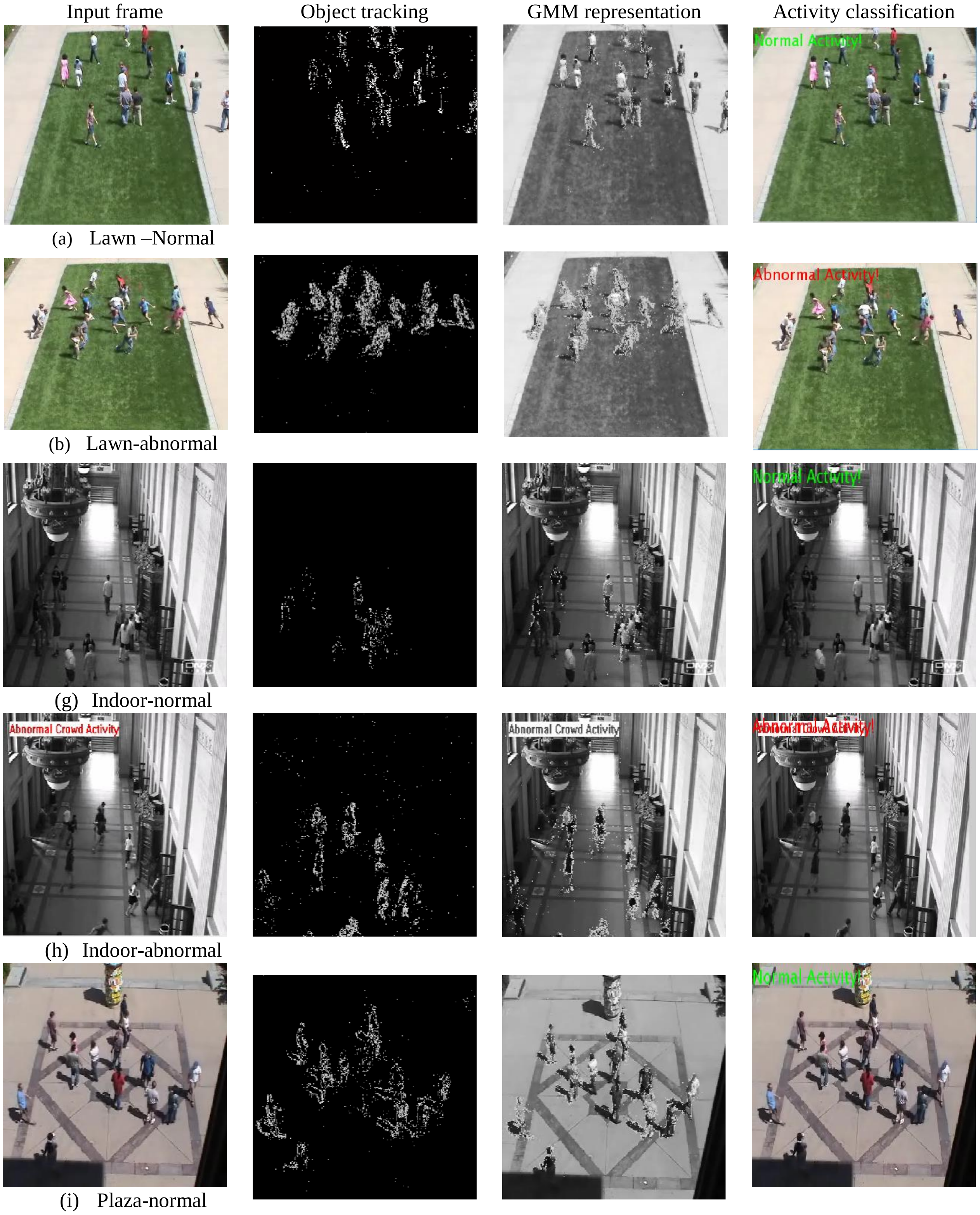


Normal activity sample	Abnormal activity sample
(a) Lawn –normal activity	(b) Lawn –abnormal activity
(c) Indoor-normal activity	(d) Indoor-abnormal activity
(e) Plaza-normal activity	(f) Plaza-abnormal activity

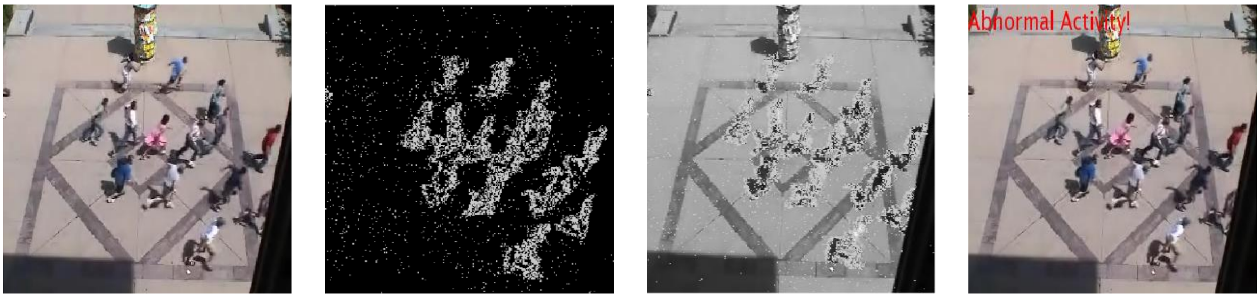
Fig. 4. Sample images from UMN dataset

Published By:
Blue Eyes Intelligence Engineering
& Sciences Publication

The UMN data contains total 7739 frames which are obtained from three different scenarios including indoor and outdoor scenes as lawn, indoor and plaza. In these scenarios, initially normal activities are displayed and later suddenly evacuation happens at the end of each scenario which is considered as abnormal activity and an abnormal or normal activity indication is displayed. Fig. 5 shows multiple stages to obtain the activity classification using proposed approach.



Published By:
Blue Eyes Intelligence Engineering
& Sciences Publication



(j) Plaza-abnormal

Fig.5. Activity classification

Above Fig. 5 shows several stage included in the proposed approach of activity classification. In order to perform this task, we have considered three scenarios where normal and abnormal frames are evaluated and activity is classified using proposed approach. First column of thee figures shows considered normal and abnormal frame for each scene. In the second column, we apply PSO and social force model based energy model for tracking the objects in the video. Third column represents the detected objects and provides the distribution model and final column of the figures shows recognized activity as normal and abnormal activity for the corresponding input frame.

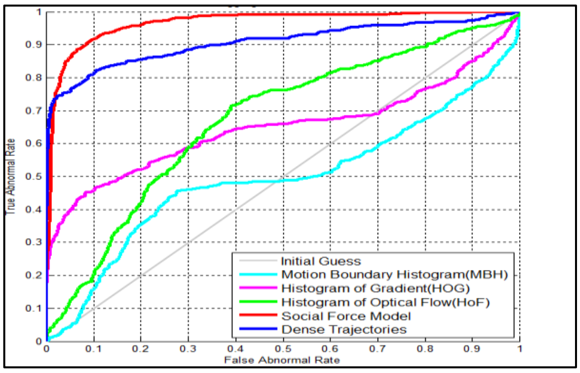


Fig. 6.ROC curve analysis

The performance of proposed approach is compared with the existing techniques of abnormal crowd behaviour detection in terms of total area under curve or ROC analysis. The proposed approach is compared with the state-of-art techniques of abnormal crowd behaviour detection which are Random Guess, Motion Boundary Histogram (MBH), Histogram of Oriented Gradients (HOG), Histogram of Optical Flow (HOF) and dense trajectory.

Moreover, the performance of proposed approach is also compared in terms of activity classification rate using the UMN dataset. Sample images of these three activities are given in Fig. 4 where outdoor 1, indoor 1 and outdoor 2 scenes are considered for analysis. The comparative analysis in terms of accuracies is given in the TABLE I.

TABLE I. Behaviour detection classification performance comparison

Video Scene	**Bayesian Model [33]**	**Force Field [34]**	**Chaotic Invariant [35]**	**Social Force Model [36]**	**Sparse reconstruction cost [37]**	**Optical Flow [38]**	**Proposed Approach**
Lawn	99.03	88.69	90.62	84.41	90.52	99.10	**99.16**
Indoor	95.36	80.00	85.06	82.35	78.48	94.85	**97.32**
Plaza	96.63	77.92	91.56	90.83	92.70	97.76	**98.66**
Average Accuracy	97	82.20	89.08	85.86	87.23	97.23	**98.38**

The above given TABLE I shows a comparative study for abnormal detection and classification. This comparative study shows that the proposed approach achieves better accuracy when compared with the existing techniques.

V. CONCLUSION

In this work, we focus on the abnormal crowd behaviour detection and classification using computer vision based video processing technique. Conventional models are based on the social force model or particle filtering methods which are not able to achieve the desired accuracy. In order to overcome this issue, we developed a novel approach in this work where particle filtering and social force modeling is combined together and clustering scheme is also applied. Later, steak line and optical flow methods are implemented for feature analysis. After feature extraction, interest point detection and tacking is performed which helps to identify the distribution of crowd in the given frame and finally, GMM based classification model is implemented which make use of threshold to identify the abnormal events. The performance of proposed approach is compared with the other schemes and it can be concluded that proposed approach achieve better performance.

REFERENCES

1. Ang, M., Rajasegarar, S. Rao, A.S., Leckie C. and Palaniswami M., "Anomalous Behaviour Detection in Crowded Scenes Using Clustering and Spatio-Temporal Features", Springer, Cham International Conference on Intelligent Information Processing, pp. 132-141, 2016.
2. Mehran R., Oyama A. and Shah M., "Abnormal crowd behaviour detection using social force model", IEEE Computer Society Conference on Computer Vision and Pattern Recognition, 2009.
3. Zhang, X., Zhang, X.F, Wang, Y. and Yu H., "Extended social force model-based mean shift for pedestrian tracking under obstacle avoidance", IET Comput, pp. 1–9, 2016.
4. Bauer D., Seer S. and Brändle N., "Macroscopic pedestrian flow simulation for designing crowd control measures in public transport after special events", Summer Computer Simulation Conference, San Diego, CA, USA, pp. 1035–1042, 2007.
5. Zhan B., Monekosso D.N., Remagnino P., Velastin S.A. and Xu, L.-Q., "Crowd analysis: a survey", Mach. Vis. Appl. 19(5–6), pp. 345–357 2008.
6. Ali S. and Shah M., "Floor fields for tracking in high density crowd scenes", Springer ECCV'08: Proceedings of the 10th European Conference on Computer Vision, Berlin, pp. 1–14, 2008.
7. A. Adam, E. Rivlin, I. Shimshoni and D. Reinitz, "Robust Real-Time Unusual Event Detection using Multiple Fixed-Location Monitors", IEEE Transactions on Pattern Analysis and Machine Intelligence, vol. 30, no. 3, pp. 555-560, 2008.
8. Chun S., and Lee C. S., "Human action recognition using histogram of motion intensity and direction from multiple views", IET Computer vision, 10(4), pp. 250-257, 2016.
9. Fan X., and Tjahjadi T., "A spatial-temporal framework based on histogram of gradients and optical flow for facial expression recognition in video sequences", Pattern Recognition, 48(11), pp. 3407-3416, 2015.
10. Feng P., Wang W., Dlay S., Naqvi S. M., and Chambers J., "Social force model-based MCMC-OCSVM particle PHD filter for multiple human tracking", IEEE Transactions on Multimedia, 19(4), pp. 725-739, 2017.
11. Luo X. B., Wang Y., Wang R. Z., and Huang X. Q., "Chaotic invariants modeling of motion patterns in multiple cameras"., IEEE Machine Learning and Cybernetics (ICMLC), International Conference, Vol. 2, pp. 726-731, 2016.
12. Kamal S., Jalal A., and Kim D., "Depth Images-based Human Detection, Tracking and Activity Recognition Using Spatiotemporal Features and Modified HMM", Journal of Electrical Engineering and Technology, 11(6), pp. 1857-1862, 2016.
13. Fu Z., Feng P., Angelini F., Chambers J., and Naqvi S. M., "Particle PHD Filter Based Multiple Human Tracking Using Online Group-Structured Dictionary Learning", IEEE Access, 6, pp. 14764-14778, 2017.
14. Singh D., and Mohan C. K., "Graph formulation of video activities for abnormal activity recognition", Pattern Recognition, 65, pp. 265-272, 2017.
15. Ijjina E. P., and Chalavadi K. M., "Human action recognition in RGB-D videos using motion sequence information and deep learning", Pattern Recognition, *72*, pp. 504-516, 2017.
16. Sabokrou M., Fayyaz M., Fathy M., Moayed Z., and Klette R., "Deep-anomaly: Fully convolutional neural network for fast anomaly detection in crowded scenes", Computer Vision and Image Understanding, 2018.
17. Gunduz A. E., Ongun C., Temizel T. T., and Temizel A., "Density aware anomaly detection in crowded scenes", IET Computer Vision, 10(5), pp. 376-383, 2016.
18. Alvar M., Torsello A., Sanchez-Miralles A., and Armingol J. M., "Abnormal behaviour detection using dominant sets", Machine vision and applications, 25(5), pp. 1351-1368, 2014.
19. Mehran R., A. Oyama and M. Shah, "Abnormal crowd behaviour detection using social force model", IEEE Conference on Computer Vision and Pattern Recognition, pp. 935- 942, 2009.
20. Wang Y and Mori G, "Human action recognition by semi-latent topic models", J. IEEE Transactions on Pattern Analysis and Machine Intelligence, Vol.31, No.10, pp. 1762-1764, 2009.
21. Monti F and Regazzoni C S, "Human action recognition using the motion of interest points", International Conference on Image processing, pp. 709-712, 2009.
22. Zhang D., Xu K., Peng H., and Shen, Y., "Abnormal Crowd Motion Behaviour Detection based on SIFT Flow", International Journal of Signal Processing, Image Processing and Pattern Recognition, 9(1), pp. 289-302, 2016.
23. Sah M., and Direkoglu C., "Semantic annotation of surveillance videos for abnormal crowd behaviour search and analysis", 14th IEEE International Conference on Advanced Video and Signal Based Surveillance (AVSS), pp. 1-6, 2017.
24. Ji Q. G., Chi R., and Lu, Z. M., "Anomaly detection and localisation in the crowd scenes using a block-based social force model", IET Image Processing, 12(1), pp. 133-137, 2017.
25. Zhang Y., Qin L., Ji R., Yao H., and Huang Q., "Social attribute-aware force model: exploiting richness of interaction for abnormal crowd detection", IEEE Transactions on Circuits and Systems for Video Technology, 25(7), pp.1231-1245, 2015.
26. Wen Y., Du J., and Lee J., "Abnormal Event Detection Based on Crowd Density Distribution and Social Force Model", International Chinese Intelligent Systems Conference Springer, Singapore, pp. 585-595, 2016.
27. Rojas O. E. and Tozzi C. L., "Abnormal Crowd Behaviour Detection Based on Gaussian Mixture Model", European Conference on Computer Vision Springer, Cham, pp. 668-675, 2016.
28. Direkoglu C., Sah M., and O'Connor N. E., "Abnormal crowd behaviour detection using novel optical flow-based features", 14th IEEE International Conference Advanced Video and Signal Based Surveillance (AVSS), pp. 1-6, 2017.
29. Zhang X., Zhang Q., Hu S., Guo C., and Yu H., "Energy level-based abnormal crowd behaviour detection", Sensors, 18(2), pp. 423, 2018.
30. Rabaud V., Belongie S., "Counting crowded moving objects", CVPR, 2006.
31. Sand P. and Teller S., "Particle video: Long-range motion estimation using point trajectories", IJCV, 2008.
32. Unusual Crowd Activity Dataset: http://mha.cs.umn.edu/Movies/Crowd-Activity-All.avi 3161,3164, 3166.
33. S. Wu, H. S. Wong and Z. Yu, "A Bayesian Model for Crowd Escape Behaviour Detection", IEEE Transactions on Circuits and Systems for Video Technology, 24(1) pp. 85– 98, 2014.
34. D. Chen and P. Huang. "Motion-based unusual event detection in human crowds", Journal of Visual Communication and Image Representation, 22(2), pp. 178-186, 2011.
35. S. Wu, B. E. Moore and M. Shah, "Chaotic Invariants of Lagrangian Particle Trajectories for Anomaly Detection in Crowded Scenes", IEEE Conference on Computer Vision and Pattern Recognition, pp. 2054-2060, 2010.
36. R. Mehran, A. Oyama and M. Shah, "Abnormal Crowd Behaviour Detection using Social Force Model", IEEE Conference on Computer Vision and Pattern Recognition, pp. 935-942, 2009.
37. Y. Cong, J. Yuan and J. Liu, "Abnormal Event Detection in Crowded Scenes using Sparse Representation", Pattern Recognition, 46(7), pp. 1851-1864, 2013.
38. Direkoglu C., Sah, M., and O'Connor N. E. "Abnormal crowd behaviour detection using novel optical flow-based features", 14th IEEE International Conference, Advanced Video and Signal Based Surveillance (AVSS), pp. 1-6, 2017.