Section A-Research paper

Branching Particle Filter for Crowd Anomaly Detection

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ABSTRACT

There is an exponential rise in the demand for automatic methods for analyzing the enormous quantities of surveillance video data generated perennially by closed-circuit television (CCTV) systems. One of the main objectives of deploying an automated visual surveillance system is to detect anomalous behavior patterns and recognize the normal ones. Lot of work has been done in this field using object tracking techniques which deploy kalman or particle filter to serve the purpose. The particle filters show good results in Nonlinear Non-Gaussian environment, thus overcoming the limitation of kalman filters but they fail to track occluded target. Thus, basic particle filters give poor results in tracking objects in crowded video sequences where there is a possibility of the target object to get occluded. The current study describes a new method of tracking an object in a video using Branching Particle filter for providing precision in tracking thereby increasing the accuracy in detecting anomalies in crowded videos.

Keywords: object tracking, Bayesian filters, motion vectors, branching particle, optical flow, anomaly detection

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INTRODUCTION

Keeping in view the vast applications of moving object detection and tracking in all walks of life, be it domestic, commercial, sports or national security, tremendous research work has been done in this field over the years. A number of methods and approaches are available for motion estimation and for tracking moving objects to detect anomalies in a video. The task of moving object detection involves feature point detection and extraction. The most frequently used appearance feature descriptors for feature analysis for the purpose of human detection include the texture, colour and geometrical shape of a person. Of these, SIFT [1], Histograms of Oriented Gradients (HOG) [2] Gabor [3], and LBP [4], are the most popular, and have emerged as widely applied feature description techniques for tracking a person and for retrieval. These descriptors follow the principle of taking raw information from the magnitude and orientations of pixel. This paper deploys the optical flow method to select interesting features such as corners to calculate the velocity vectors (motion) of the pixels at these corner points. The performance of this feature is analyzed in terms of issues such as illumination, occlusion and pose variation. Once the features are extracted the next step is to perform object tracking. The most commonly used methods for object tracking are Kalman Filter [5], Particle Filter [6], MHT [7], Template Matching [8], Mean Shift, Cam-Shift SVM [9] and many more. There are various merits & demerits of each technique. For stable & linear system having Gaussian noise, Kalman filters are preferred over others. Particle filters show good results in nonlinear non- gaussian environment thus overcoming the limitations of kalman filters but Particle Filters show poor results in crowded scenes with dynamic background. Due to the resampling step added in particle filters two problems arose. First, at each step, noise particles are also resampled leading to an increase in the noise effect on the system. Moreover, in resampling step, the particles with higher weight are carried forward and those with lesser weights are removed. After a few iterations it is observed that particles with higher weight simply crumple into one, leading to a decrease in the diversity of particles thereby diminishing the accuracy of approximation. This is called the problem of particle degeneracy and impoverishment [10]. The current study describes a new method of tracking a small crowd of moving people in a video using Branching Particle filter [11][12][13] for providing precision in tracking. In order to demonstrate the effectiveness of the proposed method, experiments were performed comparing the results with other state-of-the-art techniques. It proved that the proposed method performs well with higher accuracy in terms of target matching. Various performance parameters like precision, recall, f1 score, accuracy and area under the curve are analyzed using the branching particle filter. Since the BPF overcomes all the limitations of Kalman and Particle Filters in terms of tracking, we then proceed further to detect anomalous activity in the dataset using BPF.

RELATED WORK

Many anomaly events are unknown, predicting how an event outside the normal could occur. Therefore, it is impossible to let a model learn every anomaly event. However, it is possible to get videos with normal events from any surveillance camera because most recorded events are normal—this encouraged people to use normal videos to train their models. Michael A. Kouritzin [12] discusses a large class of discrete time branch particle filter. This work has been represented with Bayesian model or technique selection capability. Here effective resampling is canvassed or analyzed. So, the weighted particle filter basically does not have resampling. SMC algorithms are generally applied in various stages. Kouritzin brought out four new classes of the branching SMC algorithm that is basically designed to limit or bound, wide particle variations. Michael A. Kouritzin et.al [13] planned a nonlinear filtering, that is addressed with the distribution of present state and this model is used for non-observable and random dynamic signal. This signal gives description of a distorted, corrupted partial observation operation. Kouritzin [12] also brought in a novel noise deduction algorithm that is called the Chopthin algorithm. Essentially, this algorithm abides by these resampling techniques until finalized output of the new particles. Mohamed Ali et al. [29] suggested an approach to identify anomaly events by applying a convolutional autoencoder and a preprocessing for frames to extract the features. Shifeng Li et al. [14] suggested identifying anomaly events by optical flow. They needed to calculate the likelihood to know the frame is an anomaly or normal. They subtracted the background from each frame to reduce the computational cost. Zhijun Fang et al. [15] suggested identifying anomaly events by multi histogram optical flow (MHOF) and PCANet. MHOF was used to extract local low-level features. PCANet was used to extract high-level features. They used Support Vector Machines (SVM) for classification. Tian Wang et al. [16] suggested identifying anomaly events using the Hidden Markov model. They extracted features using a histogram of optical flow orientation (HOFO). Medhini G. Narasimhan et al. [17] suggested identifying anomaly events using the Gaussian classifier model. They extracted local features, matched them with Structural Similarity Index Measure (SSIM), and extracted global features using sparse autoencoders. Roberto Leyva et al. [18] suggested identifying anomaly events using the Gaussian Mixture Model (GMM). They extracted features using a histogram of optical flow (HOF). Jing Wang and Zhijie Xu [19] suggested a good real-time approach to identify anomaly events using wavelet transform. They extracted features using a statistical model. Amit Adam et al. [20] suggested an optical flow approach to identify anomaly events. This approach extracted local low-level remarks from the video. They monitored the scene with multiple, local, low-level feature monitors and saved it. They implemented low-level monitors and chose to monitor velocities and directions. In addition, they used a threshold to identify anomalies in the flow. Their algorithm needed a few minutes to collect activities and get results. In [21], Jaechul Kim et al. suggested identifying anomaly events via optical flow. They used a Mixture of Probabilistic Principal Component Analyzers (MPPCA) to identify the typical patterns. They generated a space-time Marcov Random Field (MRF), and the reason for that was enabling inference at each local site. Ramin Mehran et al. [22] suggested identifying anomaly events using the Social Force model. They were using a grid on the frame after calculating the space-time average of optical flow. After that, they used Force Flow for each pixel. Spatio-temporal volumes of Force Flow were used to know the normal event. Vijay Mahadevan et al. [23] suggested identifying anomaly events by combining the previous approaches. They combined the Social Force model with MPPCA. Matheus Gutoski et al. [24] suggested an approach to identify anomaly events by applying an autoencoder and One-class Support Vector Machines for classifications. Muhammad Asif et al. [25] suggested an approach to identify anomaly events by using Mask R-CNN with resnet101 as a backbone architecture. Cong Ma et al. [26] suggested tracking multiple objects using a novel architecture. Fariba Rezaei et al. [27] suggested an approach to identify anomaly events by using a deep convolutional neural network to train them using the extracted features from VGG-Net. Sujith Satya et al. [28] suggested a tracking model using an optimal support vector machine to recognize object behavior.

METHODOLOGY

This section elaborates the technique of detecting abnormal behavior in video frames by the process of tracking. Here the tracking has been performed by using a new class of filters called the branching particle filters. These filters come under the n- class of Bayes Filter [] which use the concept of "prediction". Thus, the normal activity of the object of interest is predicted in the next frame and any deviation between the observed and predicted behavior is considered as abnormal. The process of tracking involves the usual steps of moving object detection and tracking followed by anomaly detection. Fig. 1 below shows the general framework for tracking and anomaly detection in video using BPF.

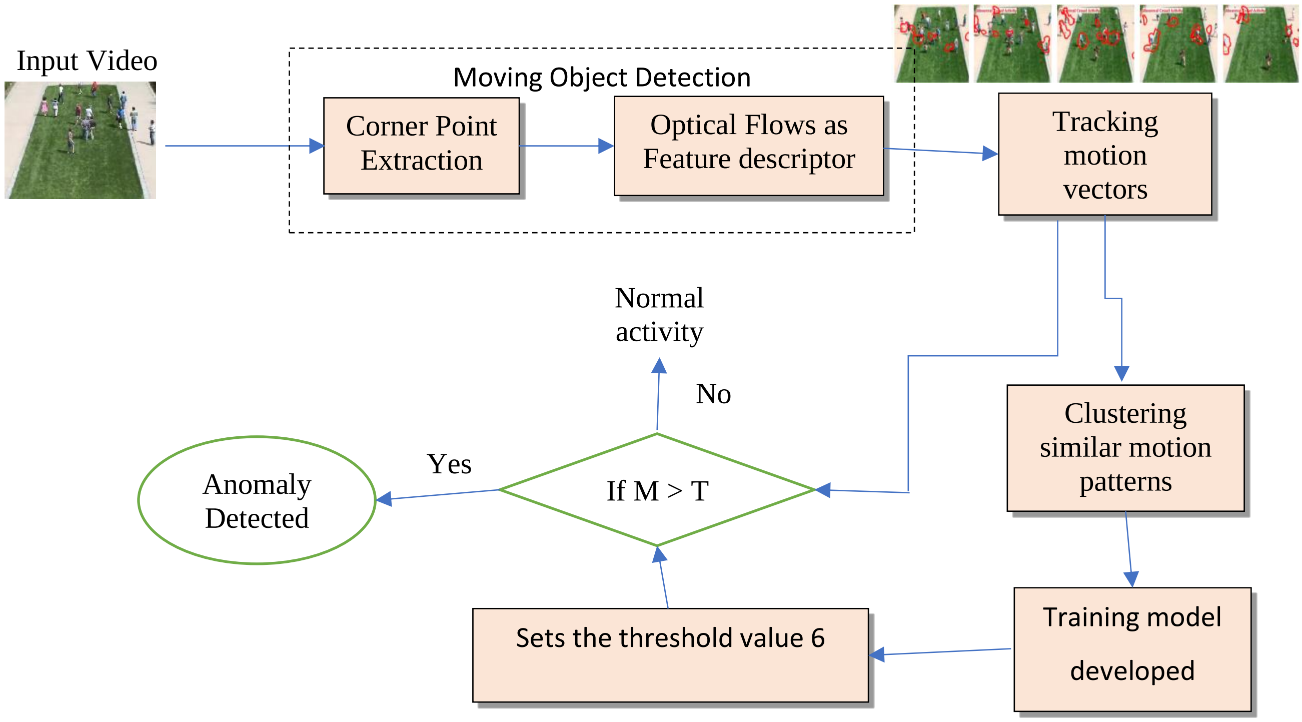


Fig. 1 Tracking and Anomaly Detection using BPF

Tracking using Branching Particle Filter

A new class of Bayesian filters [25] called the Branching Particle Filters have been deployed in this chapter for object tracking. The branching particle filters are designed to reduce variances but with different updating schemes. For the branching particle filters, the updating is via branching in small time steps. Precisely, at each time step, each existing particle will die or give birth to a random number of offspring proportional to the weight. Particles that stay on the right tract (representing by heavy weights) are explored more thoroughly while particles with unlikely trajectories/positions (represented by little weights) are not carried forward uselessly.

A generic particle filter is studied by variation of resampling process. In this process, weakest sample are eliminated instead of multiplication of fittest sample. As genetic algorithm is used for reproducing from fittest parents. This technique is used for replacing negligible weights.

In this technique partial resampling process occur in place of full resampling for long time duration and proper ratio of weight is allowed. In another case, when there is no resampling occur weighted particle filters are used & weights may be fluctuated accordingly. Similarly, in other extreme conditions, branching filters are used as alternative of particle filter when fully resampling occur. This is the integrated method for residual resampling or combined PF. A changing rate of resampling occur that would be provide effectiveness of compatibility between weighted variance increases & resampling noise whenever branching filters are used.

The uniform random variables $\{U_{kn}\}$ described by branching particle filters and the branching variables {ρkn} are obtained from BPF filters. These variables separated in two different manners

The Markov process is given as {SNn, n = 0, 1, . . .} approximates the un-normalized filter $\{\sigma_n$, n = 0, 1, . . .} in terms of the calculations as given below:

The following branching Filter process $\left\{S_p^N, p = 0{,}1 \ldots\ldots\right\}$ denotes the un-normalized filters $\{\sigma_n,\ n = 0{,}1 \ldots\ldots\}$ in respect of the calculations as follows:

Initialization:

$\{X_0^k\}_{k=1}^N$ are independent samples of $\pi_0, N_0 \coloneqq N, N_n \coloneqq 0\ L_0^k \coloneqq 1$ for $k \coloneqq 1, \ldots\ldots N$ and for all $n \in N$

Repetition: For n=0, 1,2……

(1) Weight by observation:

$$\hat{L}_{n+1}^K \coloneqq \alpha_{n+1}(X_n^k) L_n^K\ for\ k \coloneqq 1{,}2, \ldots\ldots N_n \tag{1}$$

(2) Evolve Independently:

$$Q^Y\left(\hat{X}_{n+1}^k \in \Gamma_k \forall k \middle| F_n^X \vee F_{n+1}^U\right) \coloneqq \prod_{k=1}^{N_n} K(X_n^k, \Gamma_k)\ \forall \Gamma_k \tag{2}$$

(3) Estimate

$$\alpha_{n+1}\ by\colon S_{n+1}^N \coloneqq \frac{1}{N}\sum_{k=1}^{N_n} \hat{L}_{n+1}^K \delta_{\hat{X}_{n+1}^K} and\ \pi_{n+1}(f)\ by \frac{S_{n+1}^N(f)}{S_{n+1}^N(1)} \tag{3}$$

(4) Average Weight

$$A_{n+1} \coloneqq S_{n+1}^N(1) \tag{4}$$

Repeat (13 to 14): for $k \coloneqq 1,2 \dots \dots, N_n \; do$

(5) Resampling Case:

$$\hat{L}_{n+1}^{K} \in (a_n A_{n+1}, b_n A_{n+1}) \; then \tag{5}$$

a) Offspring Number

$$N_{n+1}^{k} \coloneqq \left\lfloor \frac{\hat{L}_{n+1}^{K}}{A_{n+1}} \right\rfloor + \rho_{n+1}^{k} \; with \; \rho_{n+1}^{k} a \left(\frac{\hat{L}_{n+1}^{K}}{A_{n+1}} - \left\lfloor \frac{\hat{L}_{n+1}^{K}}{A_{n+1}} \right\rfloor \right) - Bernoulli \tag{6}$$

b) Resample:

$$\hat{L}_{n+1}^{N_{n+1+j}} \coloneqq A_{n+1}, X_{n+1}^{N_{n+1+j}} \coloneqq \hat{X}_{n+1}^{k} \; for \; j \coloneqq 1, \dots \dots, N_{n+1}^{k} \tag{7}$$

c) Add Offspring Number:

$$N_{n+1} \coloneqq N_{n+1} + N_{n+1}^{k} \tag{8}$$

(6) Non-resample Case: If

$$\hat{L}_{n+1}^{K} \in (a_n A_{n+1}, b_n A_{n+1}) \; then \; N_{n+1} \coloneqq N_{n+1} + 1, L_{n+1}^{N_{n+1}} \coloneqq \hat{L}_{n+1}^{K}, X_{n+1}^{N_{n+1}} \coloneqq \hat{X}_{n+1}^{k} \tag{9}$$

To avoid the excess noise the estimated samples are extracted before resampling process. In unbiased manner new no. of weights $L_{n+1}^{N_{n+1}}$ and particles N_{n+1} are determined by 5 & 6 step of algorithm. In this algorithm, splitting particles are determined by step 5 & for kth particle, the prior weight $\hat{L}_{n+1}^{K}$ becomes extreme and beyond this residual style branching is done. Since parents are at same locations for having the average weights becomes zero in the given conditions. In step 6, run the weighted particles as there is no extreme condition for prior weight L_{Kn+1}. The extreme condition is determined in this class of algorithm for flexibility.

So, in last observation, weighted particles are assumed with this algorithm. The proposed technique is used for duplicating & killing unlikely particles, without biasing the particles in step 3 to 5, but the total mass of particles and expected number of particles remain constant.

Simulation Results of BPF tracking

UMN video dataset (outdoor scene) is used in this chapter for demonstrating the proposed tracking scheme in effective and robust way.

The video consists of a crowd of people walking randomly outdoors. At different instances of time, the people are partially or fully occluded by each other.

Fig 2. shows the original UMN dataset at different instances i.e. different frame numbers.

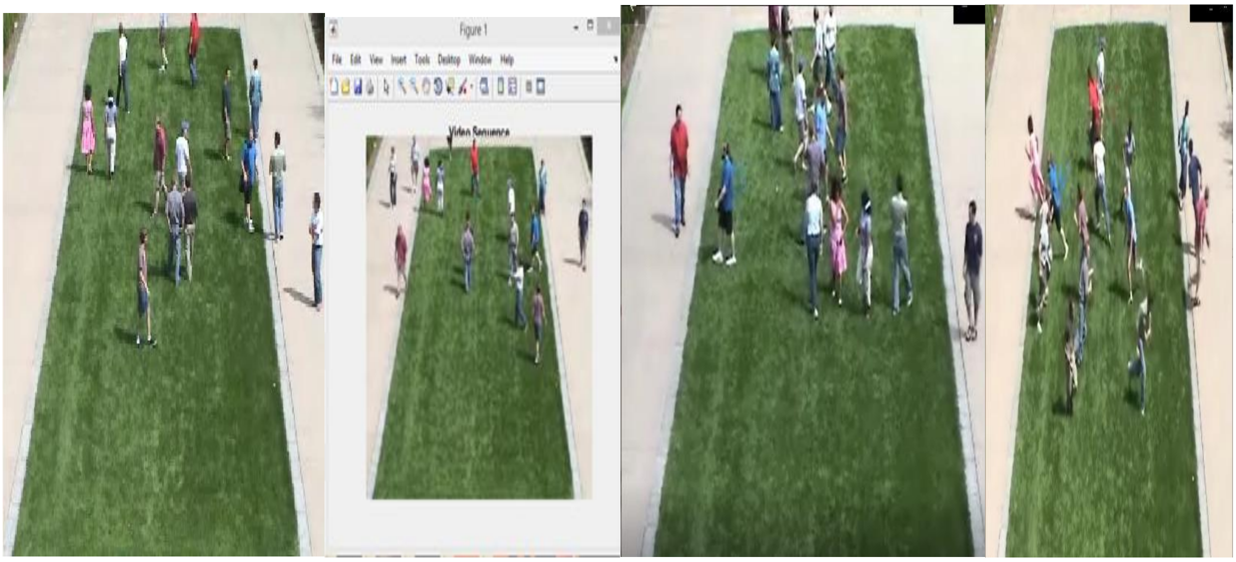


Fig. 2 UMN Dataset, Outdoor Scene

The results obtained after applying the BPF to the UMN dataset is shown below in fig 3:

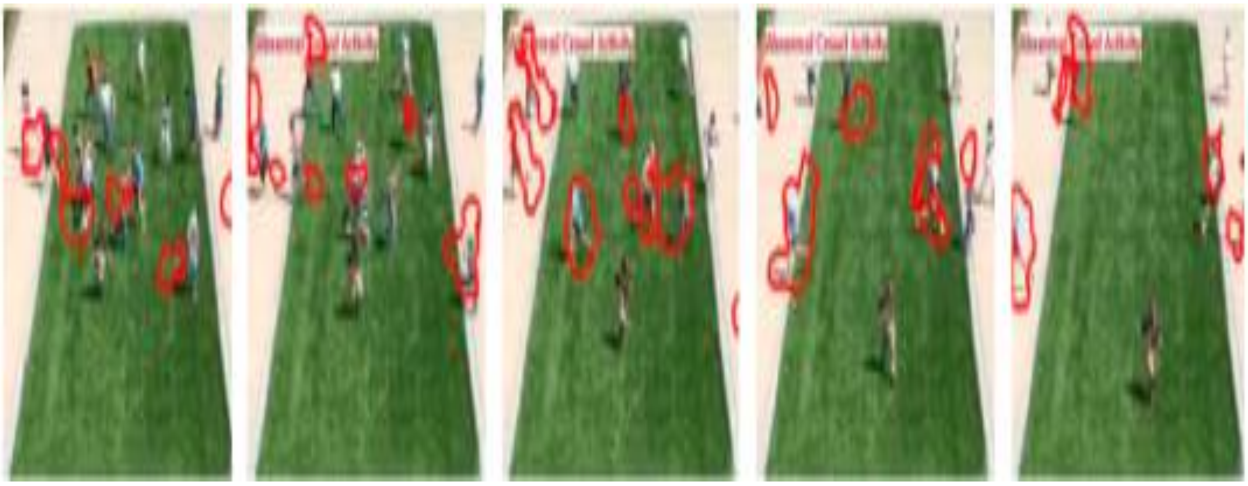


Fig. 3 Tracking Performed on UMN Outdoor Scene using BPF

The simulation results so obtained clearly show the successful tracking of target objects under different scenarios using BPF. Since the BPF overcomes all the limitations of Kalman and Particle Filters in terms of tracking, we now proceed further to detect anomalous activity in the dataset using BPF.

Anomaly Detection using BPF

Motion Descriptor

This research presents an approach to automatically detect abnormal behavior in crowd scene. For this purpose, instead of tracking every person, Harris corners are extracted as feature points to represent moving objects and tracked by optical flow technique to generate motion vectors, which are used to describe motion. This will decrease computation cost largely and retain rich motion information. Next we divide whole frame into small blocks, and motion pattern in each block is encoded by the distribution of motion vectors in it. Similar motion patterns are clustered into pattern model in an unsupervised way, and we classify motion pattern into normal or abnormal group according to the deviation between motion pattern and trained model. The results on abnormal events detection in real video demonstrate the effectiveness of the approach.

Cluster Motion Patterns

To generate pattern model, similar motion patterns are clustered in an unsupervised way. In crowd scene, it cannot be known, how many kinds of movement there will be, so the number of clusters is not known. Therefore, an on-line cluster method is deployed which does not need the number of clusters first. The initial motion pattern is taken as the first pattern model, and the deviation between all new coming motion patterns and built models is then calculated. If the smallest deviation is greater than threshold, we treat this motion pattern as a new pattern model, if not, we consider that this motion pattern belongs to one pattern model, which has smallest deviation between them.

Measurement of Similarity

We define deviation measure as follows:

$$D(i,j) = \lambda_1 (\mu_{vi} - \mu_{vj}) + \frac{\lambda_1}{\lambda_2}(\sigma_{vi}^2 - \sigma_{vj}^2) + \lambda_3 (\mu_{ri} - \mu_{rj}) + \frac{\lambda_3}{\lambda_2}(\sigma_{ri}^2 - \sigma_{rj}^2) \qquad (10)$$

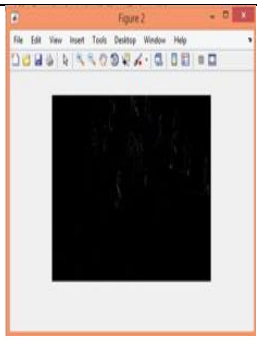
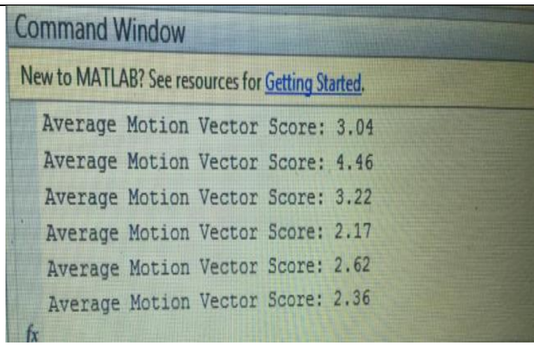
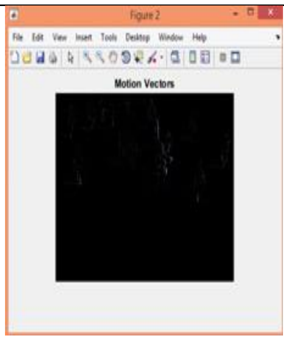
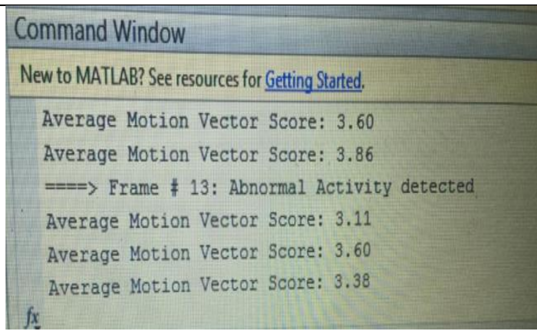
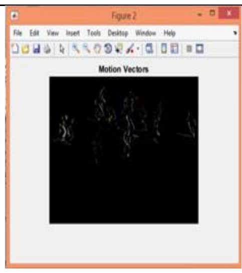
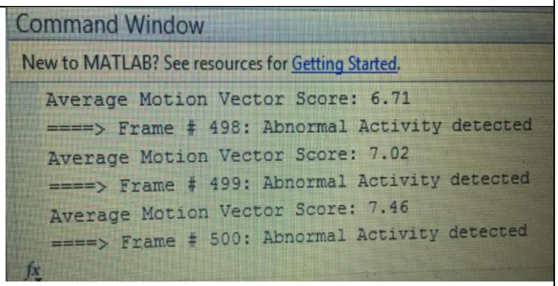
Where λ1 and λ3 is the weight of mean velocity and mean direction respectively, λ2 is the weight of variance. These parameters are mainly depending on what kinds of behavior we want to detect. If the concern is more about velocity, λ1 will greater than λ2, otherwise, λ2 will be greater. λ1 and λ2 will be similar if we are concerned both with velocity and direction. λ3 is used to keep variance weight being one third of mean weight. After models have been trained, in test stage, motion patterns are classified into normal or abnormal group according to the deviation between coming motion pattern and models. If this deviation is greater than threshold, this motion pattern is considered abnormal.

SIMULATION RESULTS OF BPF ANOMALY DETECTION

The simulation results obtained after applying Branching Particle Filters for tracking and utilizing motion vectors for deviation detection are shown in table 1.

FS1 represents the frame sequence of the actual UMN dataset, the next column gives its binary image representation followed by the average motion vector scores respectively. Since the average motion vector score lies below the threshold value except one false detection, the frame is considered to be normal.

Table 1: Simulation Results for Anomaly Detection in UMN Dataset using BPF

FRAME SEQUENCE	ORIGINAL VIDEO SEQUENCE(UMN[])	Binary Image Representation	Average Motion Vector Scores
FS1			
FS2			
FS3			

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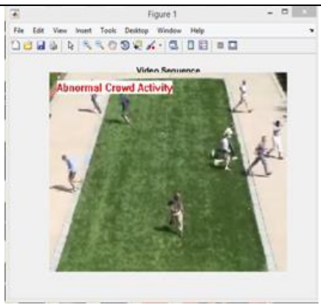
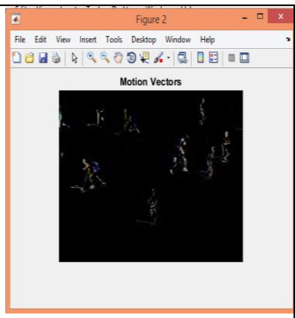
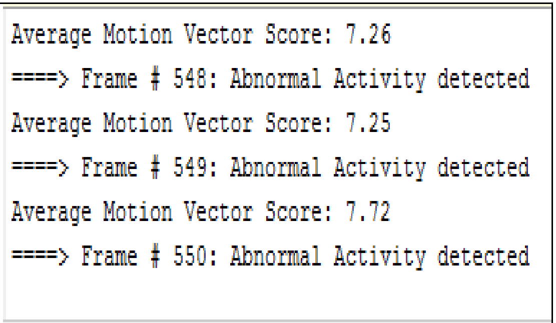
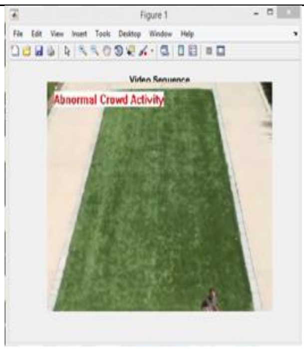
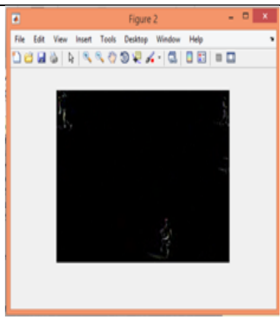
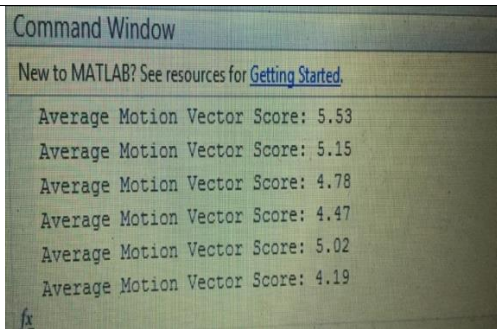
<tr><td>FS4</td><td></td><td></td><td></td></tr>
<tr><td></td><td></td><td></td><td></td></tr>
</table>

Similarly FS2 also depicts one of the original frame sequence of UMN dataset, its binary image and the average motion vector scores respectively. Again since the scores lie below the threshold, the frame is considered to have no abnormality.

FS3 shows that the people in the original frame sequence suddenly begin to run in random directions indicating some abnormal activity. As seen due to this sudden change in the kinetic velocity and direction of the motion of people, the motion vector score as calculated by optical flow technique increases beyond the threshold limit, thus indicating an anomalous activity.

Similarly the deviation of the average motion vector score from the threshold value in FS4 indicates anomalous activity where the people can be seen running suddenly in all directions.

FS5 shows the frame sequence in which the people after running in all the directions finally scatter and dissapear out of the frame. Since no motion is detected in the frame, the average motion vector score remains below the threshold value, indicating normal activity.

Performance Evaluation

The performance of the technique is evaluated with the help of various performance metrics. The simulation is performed on the system with specifications as given in Table 2.

Table 2: Simulation set up parameters

Set up parameter	**Proposal-2**
Processor	1.50GHz Intel Core i3
Operating system	Windows 8
Image type	Color Images (R,G,B)
Simulation tool	MATLAB version: R2014a
Size of Video	
Images source	UMN Video database [82]
Sample Test Images	 4.1.06 (Outdoor Scene)
Initial condition and control parameters used for key generation	[**x**=0.4523444336, **y**=0.003453324562, **z**=0.001324523564, $\overline{\mathbf{x}}$=0.002, $\overline{\mathbf{z}}$=0.004, **r**=3.9 and **β**=4.5]

The simulation results obtained after applying Branching Particle Filter to UMN video dataset indicates that BPF gives excellent tracking and anomaly detection results in linear, nonlinear and high dimensional crowd scenes, thereby overcoming the limitations of Kalman and Particle Filters. To validate the simulation results, comparison of the proposed technique with the previous state of art techniques has been accomplished, taking into account various performance metrics. The parameters of BPF have also been compared with those given by previous researchers to prove the improved performance of the proposed work.

Performance Metrics

1. **True Positives (TP)** - It is used to measure correct predicted positive values. It means actual class is present and the predicted class is also present. It is illustrated with an example as, if wolf was present and the shepherd also shouted wolf.

2. **True Negatives (TN)** - It is used to measure correct predicted negative values. It means actual class is not present and the predicted class is also not present. It is illustrated with an example as, if shepherd shouted no wolf and actually no wolf was present.
3. **False Positives (FP)** – It is used to measure both actual & predicted class. It means actual class is not present and the predicted class is present. It is illustrated with an example as, if wolf was not present but shouted wolf present.
4. **False Negatives (FN)** – It is used to measure both actual & predicted class. It means actual class is not present and the predicted class is present. It is illustrated with an example if shepherd shouts no wolf when actually the wolf was present.

The performance parameter like Recall Rate, Precision Rate, Accuracy & F-1 Score are calculated using FP, FN TP, TN.

5. **Accuracy** - Accuracy is the most intuitive performance measure and it is simply a ratio of correctly predicted observation to the total observations. **Accuracy** is the fraction of predictions our model got right. The performance of filter & algorithm is measured by Accuracy. It is defined as

The ratio of correctly predicted class to the total no. of classes or observations.

$$Accuracy = \frac{TN+TP}{TN+FN+TP+FP} \quad (11)$$

i.e., Correct predictions/ (total no of examples)

6. **Precision** - It may be defined as the ratio of correctly predicted positive class to all predicted positive classes. It means

correct fraction of detected items

$$Precision = \frac{TP}{FP+TP} \quad (12)$$

The graph in Fig. 4 shows that a precision of 89% is achieved at approximately 440 particles.

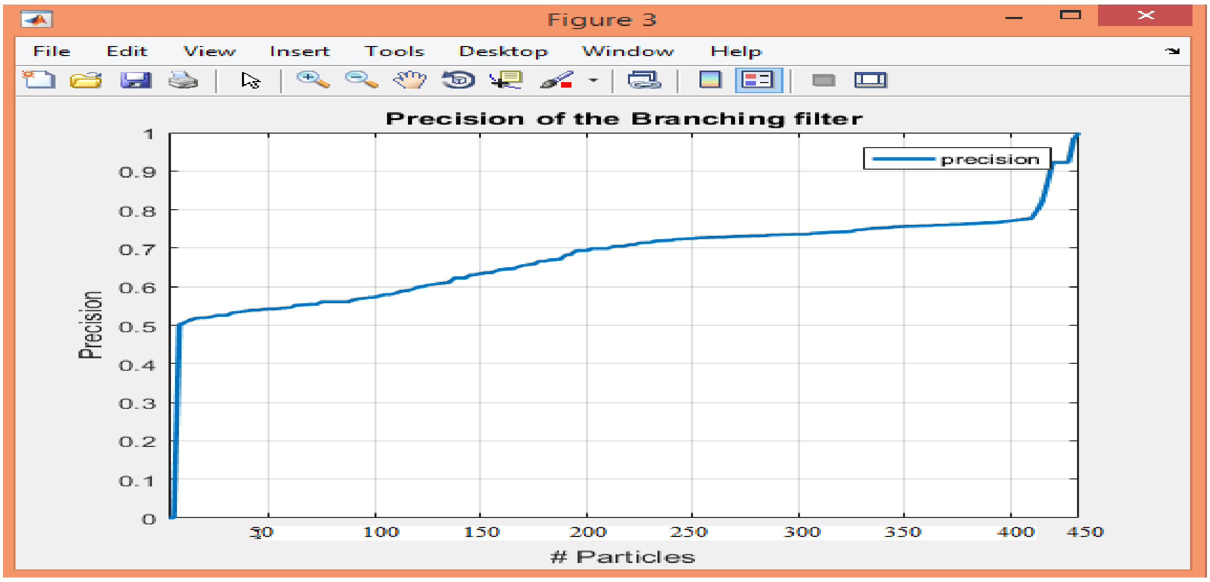


Fig. 4 Precision Vs. Number of Particles

7. **Recall** (Sensitivity) - It may be defined as the ratio of correctly predicted positive class to all actual present classes. It means correct fraction of all the detected items

$$Recall\ Rate = \frac{TP}{TP+FN} \tag{13}$$

Recall Vs. Number of particles: In Fig. 5, the graph between Recall and number of particles shows that a recall of

approximately 99% is achieved at 450 particles.

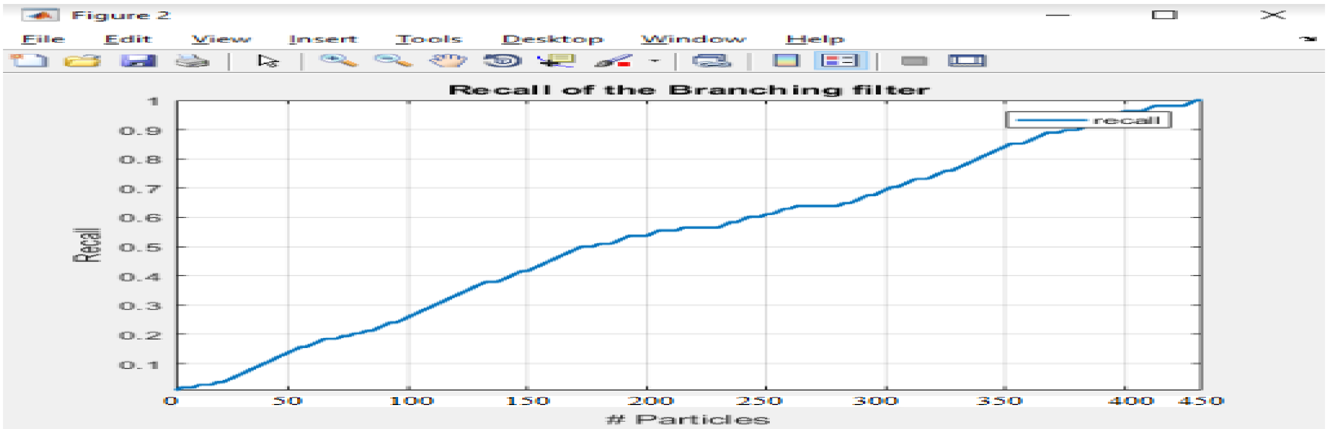


Fig. 5 Recall Vs Number of Particles

8. **F1 score -** It may be defined as average of weighted recall rate & precision rate. It means both false & true classes are measured. F1 Score is the harmonic mean of the precision and recall. It reaches its best value at 1 (perfect precision and recall).

$$F1\ Score = \frac{2*(Recall\ Rate*Precision\ Rate)}{Recall\ Rate+Precision\ Rate} \qquad (14)$$

The graph in Fig 6 below plots the F1 score with respect to number of particles. The curve shows that as the number of particles increases, F1 Score also increases. After 500 Particles iteration F1 Score becomes maximum and stable. The F1 score of the video is achieved up to 0.962. This particle number is quite less as compared to approximately 1000 particles required by particles filters. Thus, it can be concluded that Branching Particle Filters give excellent results at much lesser number of particles (approximately half the number of particles required by particle filters). This remarkably reduces the computational time and complexity of the algorithm.

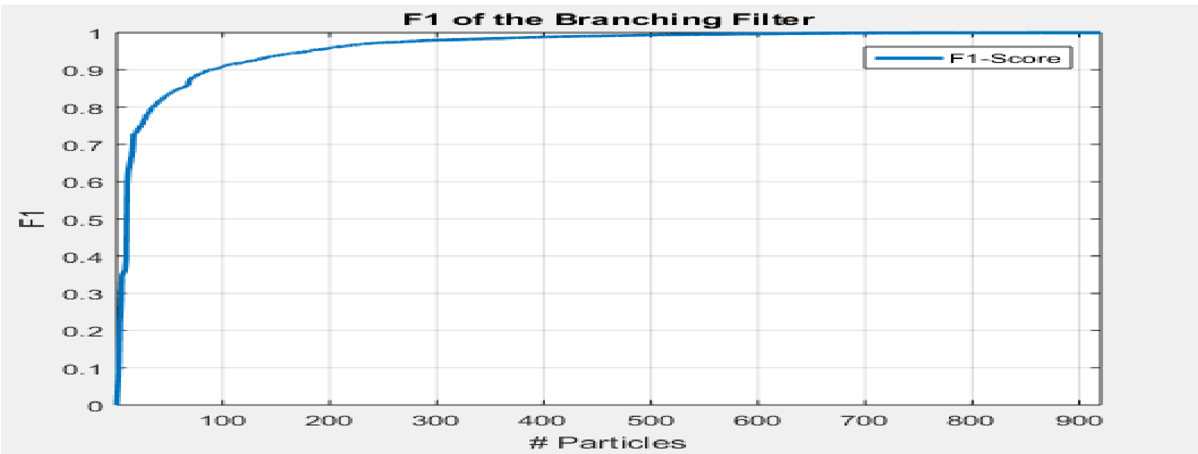


Fig. 6 F1 Score Curve

ROC and AUROC

Receiver Operator Characteristic Curve or the ROC curve is a probability curve plotted between true positive rate and false positive rate where TPR and FPR are given by the formula:

True Positive Rate = TP/TP+FN.

False Positive Rate= FP/FP+TN

In Fig. 7, the area under the ROC curve, AUROC represents degree or measure of separability. It tells how much the model is capable of distinguishing between classes. Higher the AUC, better the model is at predicting and distinguishing between classes.

Fig. 7 ROC and AUROC

The results obtained from the proposed work have further been validated by comparison with other authors in table 3. In 2017 Haider Sharif et al [26] proposed the Eigen vector approach to detect flows and events in crowd videos. The accuracy obtained by his method for UMN dataset is 92.6% as compared to 98.1% obtained from the proposed technique. This clearly indicates that the branching filter outperforms the technique of Sharif et al by giving much accurate results for anomaly detection in crowd videos.

Table 3. Performance Comparison of AUC and Accuracy for UMN Dataset

Method	**Shear Force**	**HOG/HOF**	**HOG3D**	**Cuboid3D**	**Local Motion**	**Tracklets**	**Social Force27**	**Haidar Sharif et al**	**Proposed**
AUC	0.929	0.875	0.771	0.801	0.789	0.919	0.912	0.9783	0.962
Accuracy	89.7 %	84.5%	73.3%	73.8%	76.2	85.2%	80.2%	92.6%	98.1%

Fig 8 below gives the graphical representation of the results in terms of accuracy and area under the curve obtained after comparing the proposed technique with the existing literature. The graph shows that our proposed method outperforms all the existing techniques in terms of accuracy in detecting anomalous activity in the video having highest accuracy of 98.1 %. The value of area under the curve for the proposed technique is slightly less than the eigen vector technique of Sharif et al. indicating that the proposed work may slightly lag behind the technique of Sharif et al in terms of differentiating between normal and abnormal event.

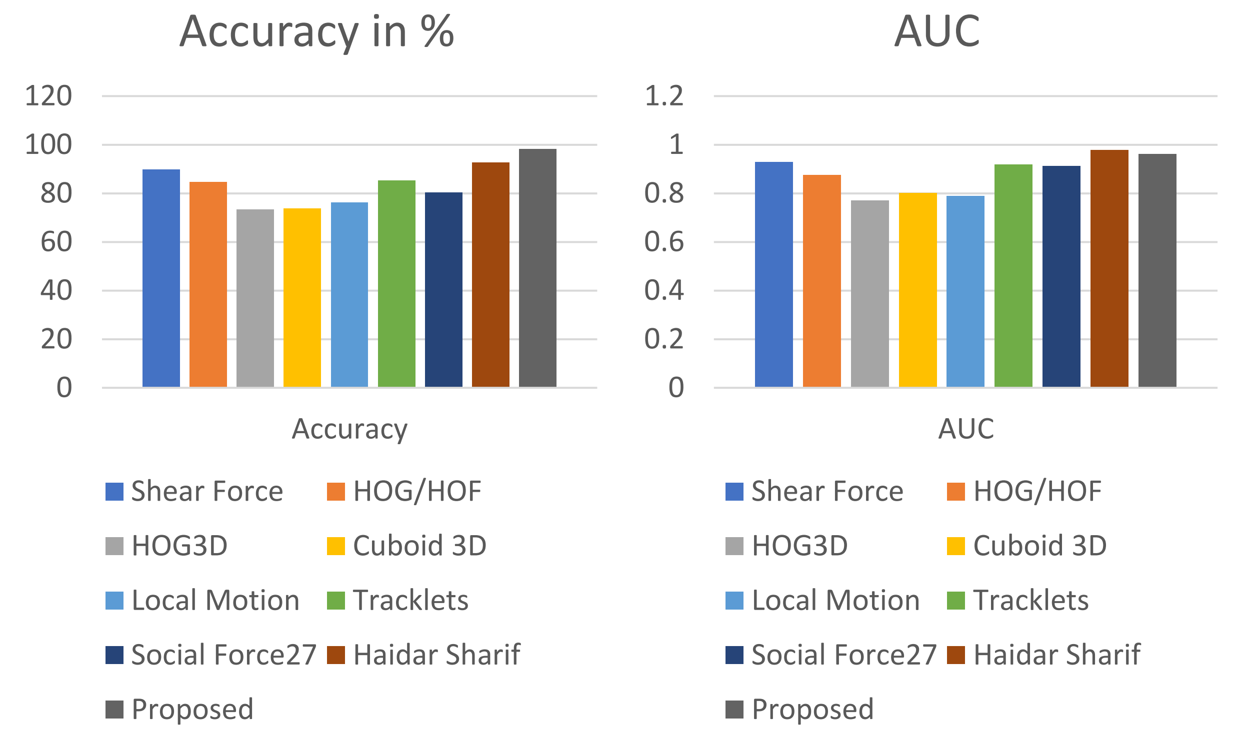


Fig. 8 Comparison of proposed BPF with previous literature on UMN dataset

Table 4 below compares the results obtained by the proposed work with the existing techniques in terms of precision, recall and f1 score.

Table 4. Performance comparison of precision recall and F score for UMN dataset

Method	**Shear Force**	**HOG/HOF**	**HOG3D**	**Cuboid3D**	**Social Force**	**Pure optical flow**	**Haidar Sharif et al**	**Ours**
Precision	0.887	0.832	0.812	0.837	0.792	0.803	0.8339	0.8876
Recall	0.912	0.878	0.793	0.810	0.891	0.822	0.8018	0.9875
F1 score	0.899	0.854	0.802	0.823	0.838	0.812	0.817	0.934

Fig 9 below gives the graphical

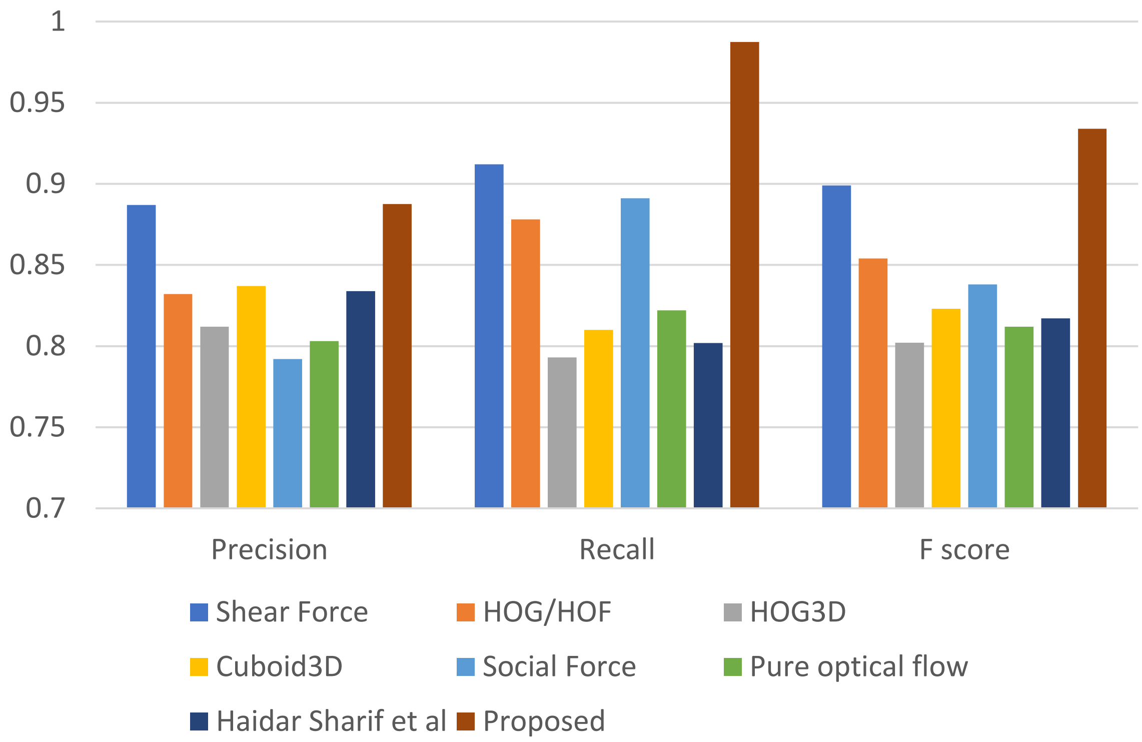


Fig. 9 Precision, recall, f score comparison

Results and Discussion

This paper deploys the Branching Particle Filter to track the object of interest. The performance of filter is evaluated by applying the filter on UMN dataset. Fig.2 shows the UMN dataset, outdoor scene which depicts a crowd of people walking randomly in all directions. The Branching Filter when applied to this dataset is successfully able to track all the people throughout the video even when the people are partially or completely occluded by each other at certain instances as shown in fig.3. Table 1. further compares the performance of the BPF with the Eigen vector approach of Haider Sharif et al on the basis of five parameters namely precision, recall and f1 score, accuracy and area under curve. Once again it is observed that the BPF outperforms the technique proposed by Haider Sharif et al. This is because the Eigen vector approach of [26] deals only with multiple separate instances of single flow occurring in videos with temporal overlap. It is not able to deal with multiple separate instances of single flow occurring in videos with no temporal overlap i.e., the crowd of people walking in random directions simultaneously. This is because for flow detection in a particular direction a specific threshold value is decided upon. If the crowd will move in any and every direction at the time of catastrophe (considered as an abnormal activity), then the eigen vector approach is not able to decide that it needs to reevaluate different threshold values every time. Moreover, the approach of [26] does not work in real time. It evaluated the parameters in offline fashion. The BPF overcomes all these issues. It is able to track and detect abnormal activity of the crowd and also works in real time.

CONCLUSION AND FUTURE SCOPE

The Branching filtering technique provides best solution to achieve maximum accuracy. Based upon the tests performed and hypothetical outcomes, it is proposed that Branching Particle Filters detect abnormal activity in crowded scene with dynamic background and partial or full occlusions, avoid the particle spread problems of the weighted-particle-filter, runs significantly faster than particle filters on tracking and other Bayesian models.

The branching particle-based filter has been found to be effective when extended to estimate the conditional distribution of multi-target signals for unknown, varying, but small numbers of targets. Thus, the branching filters does not give very good results in extremely dense or very crowded high dimensional data. Therefore, the future work will include the extension of BPF to very high dimensional data sets.

REFERENCES

1. Hou, Deyun, Lina Zeng, Junli Liang, and Kun Zhang. “Improved method for SAR image registration based on scale invariant feature transform.” IET Radar, Sonar & Navigation 2016.
2. Hsiao, Shen-Fu, Jun-Mao Chan, and Ching-Hui Wang. “Hardware design of histograms of oriented gradients based on local binary pattern and binarization.” In Circuits and Systems (APCCAS), 2016 IEEE Asia Pacific Conference on, pp. 433-435. IEEE, 2016.
3. Wu, S., Chen, Y.C., Li, X., Wu, A.C., You, J.J. and Zheng, W.S., 2016, March. An enhanced deep feature representation for person re-identification. In Applications of Computer Vision (WACV), IEEE Winter Conference on (pp. 1-8). IEEE. 2016
4. Z. Guo, L. Zhang and D. Zhang, Rotation invariant texture classification using LBP variance with global matching, Pattern Recogn. 706–719
5. L.Taylor, M. Mirdanies, R.Saputra, Optimized Object Tracking Technique Using Kalman Filter, Computer Vision and Pattern Recognition, 2021
6. J.Xiao, M. Oussalah, Robust model adaption for colour-based particle filter tracking with contextual information, Journal of Visual Communication and Image Representation, Aug 2021
7. X.Tian, H. Li, H. Deng, An improved object tracking algorithm based on adaptive weighted strategy and occlusion detection mechanism, Journal of Algorithms and Computational Techniques, January 2021.

8. Z. Li, S. Gao, K. Nai, "Robust object tracking based on adaptive templates matching via the fusion of multiple features", *Journal of Visual Communication and Image Representation*, Vol 44, April 2017, pp. 1-20
9. Z. NaNa, Z. Jin, "Optimization of Face Tracking Based on KCF and Camshift", *Procedia Computer Science*, Vol 131, 2018, pp. 158-166
10. X. Zhang, S. Yang, J. Zhang, W. Zhang, "Video anomaly detection and localization using motion-field shape description and homogeneity testing", *Pattern Recognition*, Vol 105, September 2020, 107394
11. Xu. Zhao, K. Lin, Y. Fu, Y. Hu, "Text from Corners: A Novel Approach to Detect Text and Caption in Videos", *IEEE Transactions on Image Processing*, April 2011, Vol. 20, Issue 3, pp. 790 - 799
12. M. Kouritzin, "Convergence rates for residual branching particle filters", *Journal of Mathematical analysis and Applications*, Vol 449, Issue 2, May 2017, pp. 1053-1093
13. M. Kouritzin, "Residual and Stratified Branching Particle Filters", *Computational Statistics and Data Analysis*, Vol. 111, Issue C, Feb 2016.
14. S. Kothiya, K. Mistree, "A review on real time object tracking in video sequences", *International Conference on Electrical, Electronics, Signals, Communication and Optimization*, 2015
15. Jung, J. Y., Kim, S. W., Yoo, C. H., Park, W. J., & Ko, S. J. LBP-ferns-based feature extraction for robust facial recognition. IEEE Transactions on Consumer Electroni0cs, 62(4), 446-453, 2016.
16. Feng, Jinwang, Xinliang Liu, Yongsheng Dong, Lingfei Liang, and Jiexin Pu. "Structural difference histogram representation for texture image classification." IET Image Processing 11, no. 2: 118-125, 2016.
17. Ren, Jianfeng, Xudong Jiang, and Junsong Yuan. "LBP-Structure Optimization With Symmetry and Uniformity Regularizations for Scene Classification." IEEE Signal Processing Letters 24, no. 1: 37-41, 2017.
18. Yogameena, B., S. Md Mansoor Roomi, R. Jyothi Priya, S. Raju, and V. Abhaikumar. "People/vehicle classification by recurrent motion of skeleton features." IET computer vision 6, no. 5: 442-450, 2012.
19. Chai, Zhenhua, Zhenan Sun, Heydi Mendez-Vazquez, Ran He, and Tieniu Tan. "Gabor ordinal measures for face recognition." IEEE transactions on information forensics and security 9, no. 1: 14-26, 2014.
20. Ortiz, Javier, Sławomir Bąk, Michał Koperski, and François Brémond. "Minimizing hallucination in histogram of Oriented Gradients." In Advanced Video and Signal Based Surveillance (AVSS), 2015 12th IEEE International Conference on, pp. 1-6. IEEE, 2015.

21. Kawai, Ryo, Yasushi Makihara, Chunsheng Hua, Haruyuki Iwama, and Yasushi Yagi. "Person re-identification using view-dependent score-level fusion of gait and color features." In Pattern Recognition (ICPR), 2012 21st International Conference on, pp. 2694-2697. IEEE, 2012.
22. Corvee, Etienne, Francois Bremond, and Monique Thonnat. "Person re-identification using haar-based and dcd-based signature." In Advanced Video and Signal Based Surveillance (AVSS), 2010 Seventh IEEE International Conference on, pp. 1-8. IEEE, 2010.
23. Z. Liu, Y.Zou, W. Xie, L. Li, "Multi-target Bayes filter with the target detection", *Signal Processing*, Vol 140, November 2017, pp. 69-76
24. P Ram, S. Padmavathi, "Analysis of Harris corner detection for color images", *International Conference on Signal Processing, Communication, Power and Embedded System*, 2016
25. G. Artur, S. Oksana, D. Ivan, "Anomaly Detection Using Adaptive Suppression", *Procedia Computer Science*, Vol. 156, 2019, pp. 274-282
26. Md. Haidar Sharif, "An Eigenvalue Approach to Detect Flows and Events in Crowd Videos", *Journal of Circuits, Systems, and Computers, World Scientific*, Vol. 26, No. 7 (2017) 1750110