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Performance Analysis of Branching Particle Filter for Moving Object Tracking and Anomaly Detection

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Abstract

In this paper, we demonstrate video feature representation which isimportant aspect for video anomaly detection (VAD).Research is going on to finding to perform VAD streams accurately with an acceptable false alarm rate. But due to change in nature and humanity and high space-time complexity, it is very difficult with huge video data. Abnormal event detection is practical applications of video surveillance. With problems for VAD systems on practical part: limited labeled data, ambiguous definition of "abnormal" and expensive feature engineering steps. Here, we introduce a unified detection framework to deal with these challenges using different filtering method.Here, we compare performance of Kalman filter, particle filter and branching filter. The experimental result shows that branching filter having more accuracy as compare to other filters.

Keywords: *Accuracy, Kalman filter, Branching Filter, RMSE*

I. Introduction

In recent times, security and safety concerns inpublic places and restricted areas have increased the need forvisual surveillance. Large distributed networks of many highquality cameras have been deployed and producing an enormousamount of data every second. Monitoring and processingsuch huge information manually are infeasible in practical applications.As a result, it is imperative to develop autonomoussystems that can identify, highlight, predict anomalous objectsor events, and then help to make early interventions to preventhazardous actions (e.g., fighting or a stranger dropping asuspicious case) or unexpected accidents (e.g., falling or awrong movement on one-way streets). With the widespread use of surveillance cameras inpublic places, computer vision-based scene understandinghas gained a lot of popularity amongst the CVresearch community. Visual data contains rich informationcompared to other information sources such as GPS, mobilelocation, radar signals, etc. Thus, it can play a vital role in detecting/predicting congestions, accidents and other anomaliesapart from collecting statistical information about the statusof road traffic.

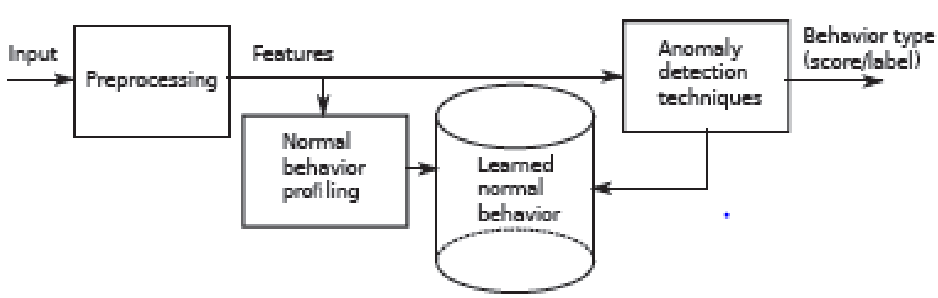

Fig.1. Overview of a typical anomaly detection scheme. Preprocessing blockextracts features/data in the form of descriptors. The normal behavior isrepresented in abstract form in terms of rules, models, or data repository.

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Specific anomaly detection techniques are used for detecting anomalies usinganomaly scoring or labeling mechanismbeen conducted focusing on data acquisition [1], featureextraction [8], scene learning [14, 36, 12], activitylearning [15], behavioral understanding [15, 16], etc. Thesestudies primarily discuss on aspects such as scene analysis,video processing techniques, anomaly detection methods, vehicledetection and tracking, multi camera-based techniquesand challenges, activity recognition, traffic monitoring, humanbehavior analysis, emergency management, event detection,etc.

Anomaly detection is a sub-domain of behavior understanding[17] from surveillance scenes. Anomalies are typicallyaberrations of scene entities (vehicles, human or theenvironment) from the normal behavior. With the availabilityof video feeds from public places, there has been a surgein the research outputs on video analysis and anomaly detection[15]. Typically anomaly detectionmethods learn the normal behavior via training. Anything deviatingsignificantly from the normal behavior can be termed asanomalous. Vehicle presence on walkways, a sudden dispersalof people within a gathering, a person falling suddenly whilewalking, jaywalking, signal bypassing at a traffic junction,or U-turn of vehicles during red signals are a few examplesof anomalies.

Branching Filters calculations are utilized in differing issues like following, expectation, constraint estimation, model alignment, grouping, Bayesian model choice and imaging (for test applications [18,17,13,9]). Fanning calculations havebit of leeway that posterity age just relies onparent notentire populace andweakness of having arbitrarily changing populaces (for example molecule numbers). As of late, Kouritzin [10]presented4 new class of expanding consecutive MC calculations that were intended to constrain wide molecule varieties.following and model choice execution of every one offour calculations was indicated tentatively to be better than an accumulation of prominent resampled molecule calculations and these four fanning calculations have much more noteworthy favorable circumstances with regards to appropriated usage (Kouritzin [12]). Be that as it may, there is little hypothesis to back up these test discoveries. Hypothetical pace of-combination results are wanted to comprehend why these do not haveautonomy and fixed molecule quantities of numerous resampled calculations so their investigation is essentially troublesome andideal union outcomes difficult to find.

The molecule channel calculation as presented in 1989 by Johan et.al. [5]. It was improved by utilizing different arbitrary factors. This gathering resampled molecule channels is one ofhuge leaps forward in enormous information successive approximation and combination properties is completely examined by numerous creators (for example Douc etal. [4]). Specifically, Chopin [2] acquired a clt forremaining development ofbootstrap calculation. Be that as it may, these molecule channels estimatedgenuine channel πn notunnormalizedσn, don't have (a similar level of) genealogical reliance asResidual Branching channel and base their resampling choices upon(areas of the) entire populace. Consequently, their investigation is very unique in relation to what is required forResidual Branching molecule channel. Be that as it may, a few new (at any rate to molecule sifting) thoughts including branching molecule channel coupling, utilization of interminable spreading molecule frameworks, utilization of following frameworks and Hoeffding-disparity based molecule framework jumping are likewise used.

The paper is organized in the sequence as introductory part is given in section I. Section II is concerned about past work. Proposed Branching filter methodology & algorithm is as shown in section III. Section IV defines the result analysis & at the last conclusion is in section V.

II. Literature Survey

To date, many attempts have been proposed to build up video anomaly detection systems [1]. Two typical approaches are: supervised methods that use the labels to cast anomaly detection problem to binary or one-class classification problems; and unsupervised methods that learn to generalize the data without labels, and hence can discover irregularity afterwards. Here, we provide overview of models in these two approaches before discussing the recent lines of deep learning and energy-based work for video anomaly detection.

The common solution in the supervised approach is to train binary classifiers on both abnormal and normal data.[13] firstly extracts combined features of interaction energypotentials and optical flows at every interest point before training Support Vector Machines (SVM) on bag-of-word representation of such features. [14] use a binary

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classifier on the bag-of-graph constructed from Space-Time Interest Points (STIP) descriptors [15]. Another approach is to ignore the abnormal data, and utilize normal data only to train model.

For example, Support Vector Data Description (SVDD) [16] first learns the spherical boundary for normal data, and then identifies unusual events based on the distances from such events to the boundary. Sparse Coding [17] and Locality-Constrained Affine Subspace Coding [18] assume that regular examples can be presented via a learned dictionary whilst irregular events usually cause high reconstruction errors, andthus can be separated from the regular ones. Several methodssuch as Chaotic Invariant [19] are based on mixture models and estimatethe probability of an observation to be abnormal for anomalydetection. Overall, all methods in the supervised approachrequire labor-intensive annotation process, rendering them lessapplicable in practical large-scale applications.

The unsupervised approach offers an appealing way to train models without the need for labeled data. The typical strategy is to capture the majority of training data points that are assumed to be normal examples. One can first split a video frame into a grid and use optical flow counts over grid cells as feature vectors [20]. Next the Principal Component Analysis works on these vectors to find a lower dimensional principal subspace that containing the most information of the data, and then projecting the data onto the complement residual subspace to compute the residual signals. Higher signals indicate more suspicious data points. Sparse Coding, besides being used in supervised learning as above, is also applied in unsupervised manner wherein feature vectors are HOG or HOF descriptors of points of interest inside spatiotemporal volumes [21]. Another way to capture the domination of normality is to train One-Class SVM (OC-SVM) on the covariance matrix of optical flows and partial derivatives of connective frames or image patches [22]. Clustering-based method [23] encodes regular examples as codewords in bag-of video- word models. An ensemble of spatio-temporal volumes is then specified as abnormality if it is considerably different from the learned codewords. To detect abnormality for a period in human activity videos, [24] introduces Switching Hidden Semi-Markov Model based on comparing the probabilities of normality and abnormality in such period. All aforementioned unsupervised methods, however, usually rely on hand-crafted features, such as gradients [23], HOG[21], HOF [21], optical flow based features [20], [22]. In recent years, the tremendous achievement in various areas of computer vision [25] has motivated a series of studies exploring deep learning techniques. Many deep networks have been used to build up both supervised anomaly detection frameworks such as Convolutional Neural Networks (CNN) [26], Generative Adversarial Nets (GAN) [27], Convolutional Winner-Take- All Autoencoders [28] and unsupervised systems such as Convolutional Long-Short Term Memories [29], [30], [31], Convolutional Autoencoders [29], [30], [32], [33], Stacked Denoising Autoencoders [34]. By focusing on unsupervised learning methods, in what follows we will give a brief review of the unsupervised deep networks.

By viewing anomaly detection as a reconstruction problem, Hasan et al. [33] proposed to learn a Convolutional Autoencoder to reconstruct input videos. They show that a deep architecture with 12 layers trained on raw pixel data can produce meaningful features comparable with the hand-crafted features of HOG, HOF and improved trajectories for video anomaly detection. [32] extends this work by integrating multiple channels of information, i.e., raw pixels, edges and optical flows, into the network to obtain better performance. Appearance and Motion Deep Nets (AMDNs) [34] is a fusion framework to encode appearance in videos. Three Stacked DenoisingAutoencodersare constructed on each type of information (raw patches and optical flows) and their combination. Each OCSVM is individually trained on the encoded values of each network and their decisions are lately fused to form a final abnormality map. To detect anomaly events across the dimension of time, [31] introduces a Composite Convolutional Long- Short Term Memories (Composite Conv LSTM) that consists of one encoder and two decoders of past reconstruction and future prediction. The performance of this network is shown to be comparable with ConvAE [33]. Several studies [29], [30] attempt to combine both ConvAE and ConvLSTM into the same system where ConvAE has responsibility to capture spatial information whilst temporal information is learned by ConvLSTM. Although deep learning is famous for its capacity of feature learning, not all aforementioned deep systems utilize this powerful capacity, for example, the systems in [32], [34] still depend on hand-crafted features in their designs.

Since we are interested in deep systems with the capacity of feature learning, we consider unsupervised deep detectors working directly on raw data as our closely related work, for example, Hasan et al.'s system [33], CAE

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[32], Composite ConvLSTM [31], ConvLSTM-AE [29] and Lu et al's system[30]. However, these detectors are basically trained with theprinciple of minimizing reconstruction loss functions instead of learning real data distributions. Low reconstruction error in these systems does not mean a good model quality because of overfitting problem. As a result, these methods do not have enough capacity of generalization and do not reflect the diversity of normality in reality.

Our proposed methods are based on energy-based models, versatile frameworks that have rigorous theory in modeling data distributions. In what follows, we give an overview of energy-based networks that have been used to solve VAD in particular.

Restricted Boltzmann Machines (RBMs) are one of the fundamental energy-based networks with visible and hidden layer. In [35], its variant for mixed data is used to detect outliers that are significantly different from the majority. The free-energy function of RBMs is considered as an outlier scoring method to separate the outliers from the data. Another energy-based network to detect anomaly objects is Deep Structured Energy-based Models (DSEBMs)[36]. DSEBMs are a variant of RBMs with a redefined energy function as o/p of a deterministic deep NN. Since DSEBMs are trained with Score Matching [37], they are essentially equivalent to one layer Denoising Autoencoders [38]. For video anomaly detection, Revathi and Kumar [39] proposed a supervised system of four modules. The last module of classifying a tracked object to be abnormal or normal is a deep network trained with DBNs and fine-tuned using a back-propagation algorithm.

III. Branching Filter Model

The moving article is recognized by methods for movement estimation to figuresituation ofmoving item invideo plane. To recognizesquares containing moving article limits by utilizingdata ofmovement vector field. Another calculation of moving articles recognition and depiction is proposed to recognize and followmoving item in video. In light ofexamination of projection of3D exhibit movement of articles,data of movement field is abused to make moving item identification increasingly effective.discontinuities of movement vector field onlimits of moving items empower us to identifymoving articles obstructs in whichpotential limits ofmoving articles find.further refinement oflimit of moving items and effective descriptor for moving articles are proposed also.

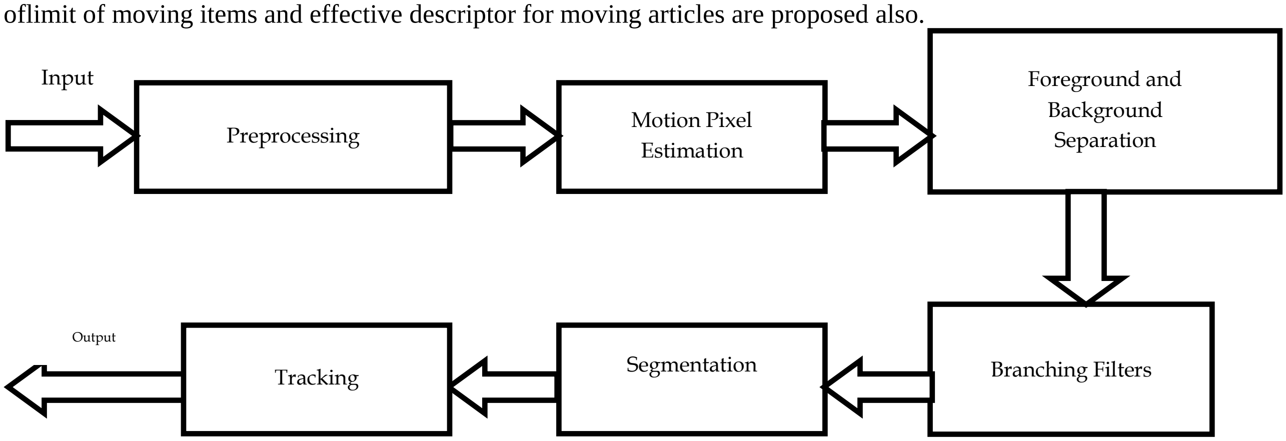

Fig 2 Proposed Methodologies

C. Preprocessing

Extracting the points from an image that gives the best define of an object in an image namely key-points (High Intensity Pixels) is very important and valuable. These points have many applications in image processing like object detection. Before detecting the anomalies, pre-processing of the video is performed. The three layered color (RGB) image is converted togrey colored image inframes.

D. Motion Pixel Estimation

Firmly identified with movement estimation is optical stream, wherevectors compare toapparent development of pixels. Moving estimationcareful 1:1 correspondence of pixel positions isn'tnecessity. Applyingmovement vectors

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topicture to integratechange tofollowing picture is called movement pay.blend of movement estimation and movement pay iskey piece of video pressure as utilized by MPEG 1, 2 and 4 just as numerous other video codecs.

E. Calculations

The techniques for discovering movement vectors can be ordered into

1) Pixel based techniques ("direct")
2) Feature based techniques ("circuitous").

F. Direct Methods

1) Block-coordinating calculation
2) Phase connection and recurrence space strategies
3) Pixel recursive calculations
4) Optical stream

G. Backhanded Methods

Backhanded strategies use highlights, for example, corner recognition, and match relating highlights between edges, formost part withfactual capacity connected overnearby or worldwide region.reason forfactual capacity is to expel matches that don't relate togenuine movement. Another calculation of moving items location and portrayal is proposed to recognize and followmoving article in video. In light ofinvestigation of projection of3D exhibit movement of items,data of movement field is misused to make moving article identification increasingly effective.further refinement oflimit of moving items and proficient descriptor for moving articles are proposed too. Asperfect imaging model, point of view projection model is embraced in this proposed framework. Calculatefirst pixel value offirst frame named as p1 andfirst pixel value ofsecond frame and named as p2.Findmean value, add allpixel values in allframes.

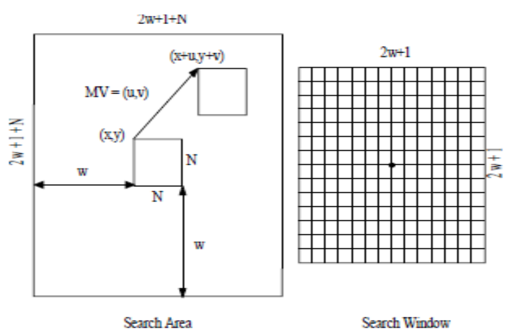

Figure 3 : Moving pixel compensation

H. Foreground and Background Separation

Foundation subtraction, otherwise called Foreground Detection, isprocedure infields of picture preparing and PC vision.Pictureareas of intrigue are objects in its closer view. Afterphase of picture pre-preparing object localisationis required which may utilize this procedure. Method of reasoning inmethodology is that of recognizingmoving articles fromcontrast betweenpresent casing andreference outline, frequently called "foundation picture", or "foundation model". Foundation subtraction is formost part done ifpicture being referred to ispiece ofvideo stream. Foundation subtraction gives significant prompts to various applications in PC vision,

J. Otsu's Thresholding

Otsu's technique is used to naturally achieve bunching based imagethresholding, decrease ofdark level image toparallel image.calculation contains bi-modular histogram (closer view pixel and foundation pixels), andideal limit isolatingtwo classes withgoal that their joined spread (intra-class fluctuation) is negligible.augmentation offirst strategy to staggered thresholding is Multi Otsu technique.

K. Proposed Tracking Algorithm

Expanding molecule technique is perceived in nonlinear separating plan, un-standardized ideal channel PT (ϕ), that isanswer of Eq. (1), which is determined by Eq. (2).

$d_{PT}(\varphi) = P_T(A\varphi)dT + P_T(h^*\varphi)dY_T$……………………………………………... (1)

$\bar{E}\left[\varphi(X_T)exp\left(\int_0^T h^*(X_s)dY_x - \frac{1}{2}\int_0^T h^*(X_s)h(X_s)ds\right)|yr\right]$……………………….. (2)

Where hope is considered identifying with degree P that imprints YTBrownian movement. Forreason that one solicitations to assess combination E[|YT] identifying with measure P. In any case, this articulation conveysrecursive connection to build upscientific arrangement; we will makeprogression of fanning molecule plans Um by methods for in that might be confirmed to strategyarrangement pT , which is

$\lim_{n\to q} U_m(T) = pT$……..…………………………………….………..…….. (3)

Let $\{U_m(T), F_T; 0 \le T \le 1\}$ beseries of branching particle schemes on (Ω, F, P) Preliminary condition is specified as

- At timei⁄m,movement involvesoccupation proportion of m_m (i⁄m) particles of mass 1/m m_m (i⁄m) connotes number of components alive at time T.
- All throughinterim, molecule voyages confidently with comparative principle as in framework Eg. (1). Let Z(s),s∈[i⁄m,((i+1))⁄m] bebend ofvague molecule, all through this interim

$dX_T = f(X_T)dT + \alpha(X_T)dW_T$…………………………………..……..…….. (4)

The mean number of offsprings for particle is given by

$\mu_m^i = E(\varepsilon_m^i) = exp\left(\int h^*\big(Z(T)\big)dY_T - \frac{1}{2}\int h^*h\big(Z(T)\big)dT\right)$…………………..…… (5)

Accordingly, fluctuation vim (V) is irrelevant, where difference occur asresult ofoff-adjusting of vim (V) to compute numeral worth _im.character * symbolizes complex conjugate. Assurance ofnumber _i m of posterity by

$$\varepsilon_m^i = \begin{cases} [\mu_m^i] & with\ probability\ \mu_m^i - [\mu_m^i] \\ [\mu_m^i] + 1 & with\ probability\ 1 - \mu_m^i + [\mu_m^i] \end{cases} \text{……………………..…….. (6)}$$

where [] representsrounding operator.

Proposed Branching Filters

In this area, we presentclass of spreading molecule channels. We never again essentially have full resampling yet rather permit fractional resampling and weight proliferation. We haveweighted molecule channel where no resampling happens and loads are constantly proliferated. Inother outrageous case, we havecompletely resampled molecule channel that can be think of as different option in contrast tolingering resampling or consolidated resampling molecule channel. As middle of, we haveentire class of branching molecule channels withadaptable measure of resampling that bearssuccessful tradeoff between weight difference increment and resampling clamor.

We first depict branching molecule channels in quitewhile of uniform irregular factors {Uk n} used to makefanning factors {ρk n} in 2 distinct method. Branching method have following steps{SNn,n = 0, 1, . . .} approximatesunnormalized filter in terms ofobservations as follows:

The following branching Filter process $\{S_n^N, n = 0,1 \dots\dots\}$ approximatesunnomatized filter $\{\sigma_n,\ n = 0,1 \dots\dots\}$ in terms ofobservations as follows

Start: $\{X_0^k\}_{k=1}^N$ are independent samples of $\pi_0, N_0 \coloneqq N, N_n \coloneqq 0 n \in N \& L_0^k \coloneqq 1$ for $k \coloneqq 1, \dots\dots N$.

Repeat: for $n \coloneqq 0,1,2 \dots\dots do$

(1) Observed Weight : $\hat{L}_{n+1}^K \coloneqq \alpha_{n+1}(X_n^k)L_n^K\ for\ k \coloneqq 1,2, \dots\dots N_n$
(2) Evolve Independently:

$$Q^Y\left(\hat{X}_{n+1}^k \in \Gamma_k \forall k | F_n^X \vee F_{n+1}^U\right)$$

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

(4) Average Weight $A_{n+1} := S_{n+1}^N(1)$
Recall again step 5 &6 : for $k := 1,2 \dots \dots, N_n$ do

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

a) Offspring Number $N_{n+1}^k := \left\lfloor \frac{\hat{L}_{n+1}^K}{A_{n+1}} \right\rfloor + \rho_{n+1}^k$ $with$ $\rho_{n+1}^k a \left(\frac{\hat{L}_{n+1}^K}{A_{n+1}} - \left\lfloor \frac{\hat{L}_{n+1}^K}{A_{n+1}} \right\rfloor\right) - Bernoulli$

b) Resample: $\hat{L}_{n+1}^{N_{n+1+j}} := A_{n+1}, X_{n+1}^{N_{n+1+j}} := \hat{X}_{n+1}^k$ for $j := 1, \dots \dots, N_{n+1}^k$

c) Addition off springing No.: $N_{n+1} := N_{n+1} + N_{n+1}^k$

(6) Without Again Sampling : If $\hat{L}_{n+1}^K \in (a_n A_{n+1}, b_n A_{n+1})$ $then$ $N_{n+1} := N_{n+1} + 1, L_{n+1}^{N_{n+1}} := \hat{L}_{n+1}^K, X_{n+1}^{N_{n+1}} := \hat{X}_{n+1}^k$

We remove our gauge before resampling to maintainstrategic distance from overabundance clamor. Key advances (5, 6) decidenew number of particles N_(n+1) and loads L_(n+1)^(N_(n+1)) inimpartial way. Atpoint whenearlier weight L ̂_(n+1)^K for molecule k is extraordinary we do lingering style fanning, parting particles as deterministically as conceivable in (5).outcome is at least zero particles all havingnormal load atsimilar area asparent. Atpoint whenearlier weight L ̂_(n+1)^K isn't outrageous we runweighted molecule venture in (6).adaptability in this class of calculations is by they way we decide "extraordinary"..

We are notfirst to utilize branching molecule channels for following. In any case, our calculations contrast to our objectives are additionally extraordinary. Inwake of building upproper limits on Nn+1 in Theorem 2 to pursue, we can without much ofstretch see that this calculation is likewise O(N). In fact,cautious examination of this calculation toearlier ones leads us toconviction thatsteady inferred inO(N) documentation for branching calculation might be less than other methods, particularly whensampling again situations does not happen time after time. We will set up this reality tentatively beneath. Since σn is assessed both model choice and separating should be possible atsame time without includingextra advance.

IV. Simulation and Results

Viable parallelization of resampled molecule channels is troublesome. These are the factors more to pick our expanding molecule channels oversampling again ones as they havesolid favorable position while simultaneously (as will be appeared in next work). In any case, we can likewise consider all calculations with one machine executions on following issues and on design determination.Remainder of this segment is composed as pursues: We initially present2 basic issues, Testing issueand limits onlyissues that will be utilized for correlation issue. At that point, we look atdifferent sampling again molecule frameworks talked about above on these issues. Next, we think aboutmost noticeably terrible of our fanning calculations tobest resampled molecule framework examined above and show even this most essential expanding calculation altogether beats all resampled molecule frameworks. At long last, we contrast all our expanding calculations with figure out which variety plays outbest. For consistency, all outcomes in this are eitherrun ofmill way ornormal more than 200 distinctive example ways of 100 edges ofvideo. We decrease no. of time ventures from 500 in result down to 3.5 asresult ofwastefulness ofother bootstrapped and other sampling molecule frameworks. We could have effectively viewed aslot bigger no. of steps inevent that would just running our channels. Be that as it may, it took us weeks to get recreations we required forsampling again molecule frameworks on our constrained PC assets.

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Fig 4 Frame of Video

For Analysis of Videos, Each video divided into frames & frames into the images and images into pixels for proper analysis. In proposed work, we analysis a data set with 200 samples.

Table 1 Performance Parameter

Sr. No.	Parameter	Value
1.	Elapsed Time	0.139937
2.	Total True Positive	165/173
3.	Total True Negatives	8/173
4.	Average Precision Rate	98.515 %
5.	F1 score (Branching Filter)	0.962
6.	RMSE (Branching Filter)	1.816
7.	Accuracy(Branching Filter)	98.182 %

The different performance parameters arecalculated in table 1. It indicates that elapsed time is 0.139937 sec. The other performance parameter, true positive, true negative, Average Precision Rate is 95.73 % , 4.62 % , 98.515 % respectively.

The F1 score of the video is achieved up to 0.962. Similarly RMSE, Accuracy of the videos is 1.816 and 98.182 % respectively.

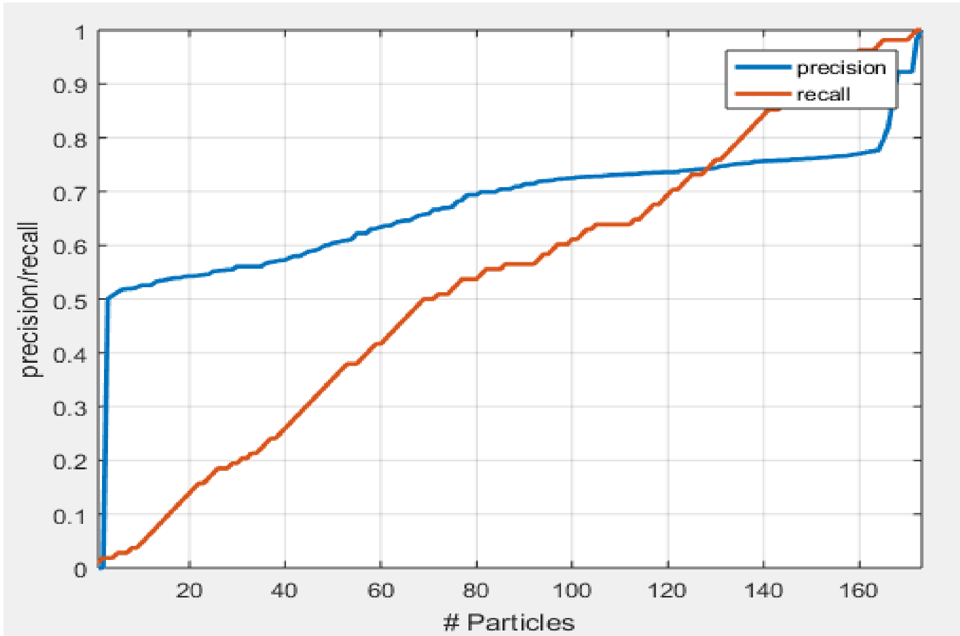

Fig 5 Comparative Analysis of Recall Rate & Precision Rate

The comparative analysis of precision rate and recall rate (figure 5).Analysis is done for 170 Particles. Initial precision rate is more dominant, after 125 particles recall rate recall rate becomes more dominant as compare to recall rate.

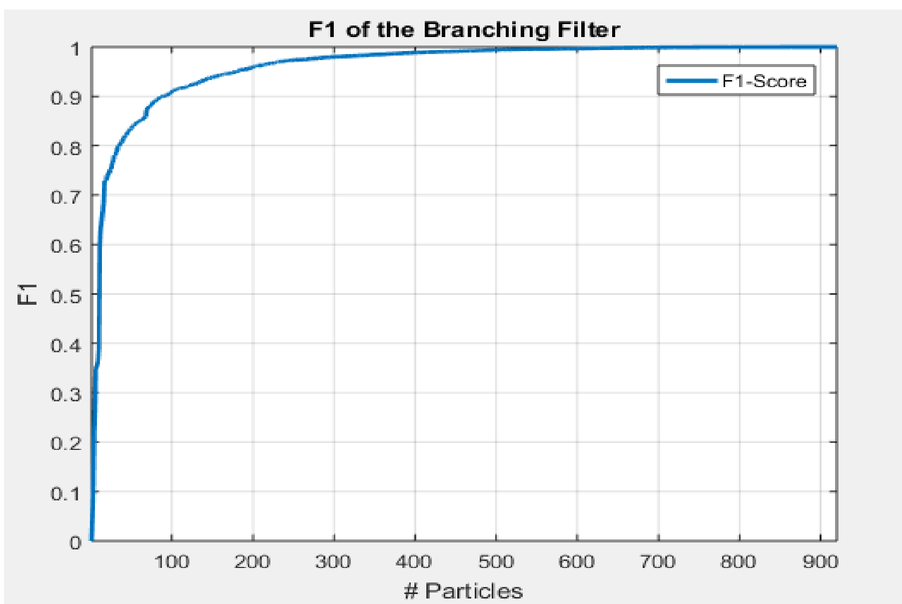

Fig 6 F1 Score in Branching Filter

The maximum F1 score of branching filter is 1. . As no. of Particles is increases F1 Score is also increase. After 500 Particles iteration F1 Score becomes maximum and stable. . The F1 score of the video is achieved up to 0.962

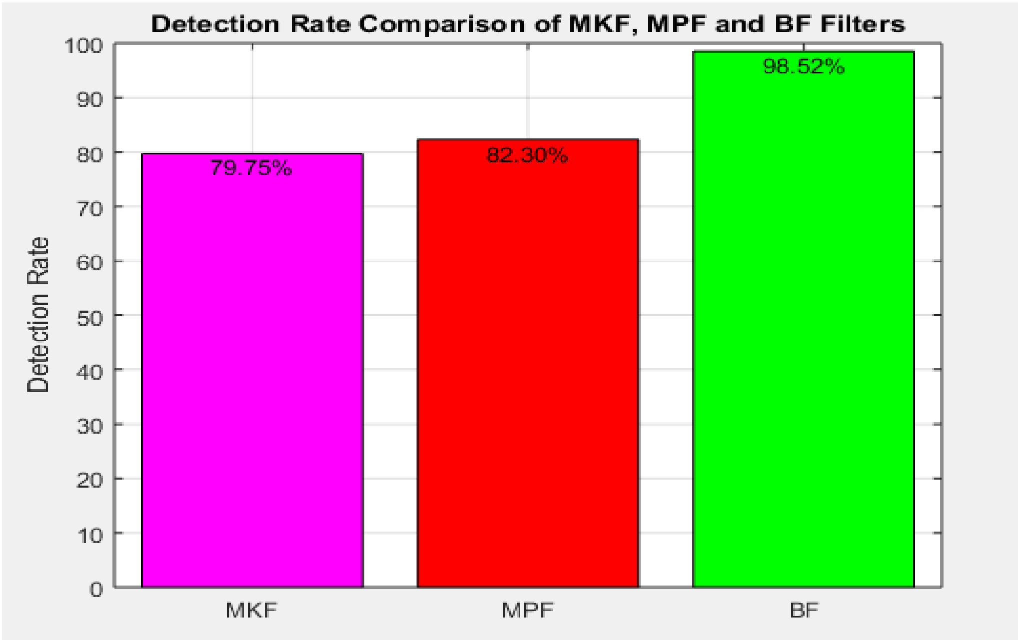

Fig 7 Detection Rate Comparative Analysis

The analysis of video stream is denoted with the performance parameter detection rate. The detection rate of a video is compareBranching Filter with Kalman filter, Particle filter. The detection rate of Kalman Filter, Particle Filter and Branching are 79.75 % , 82.30 % and 98.52 % respectively. It means branching filters are more effective as compare to other methods

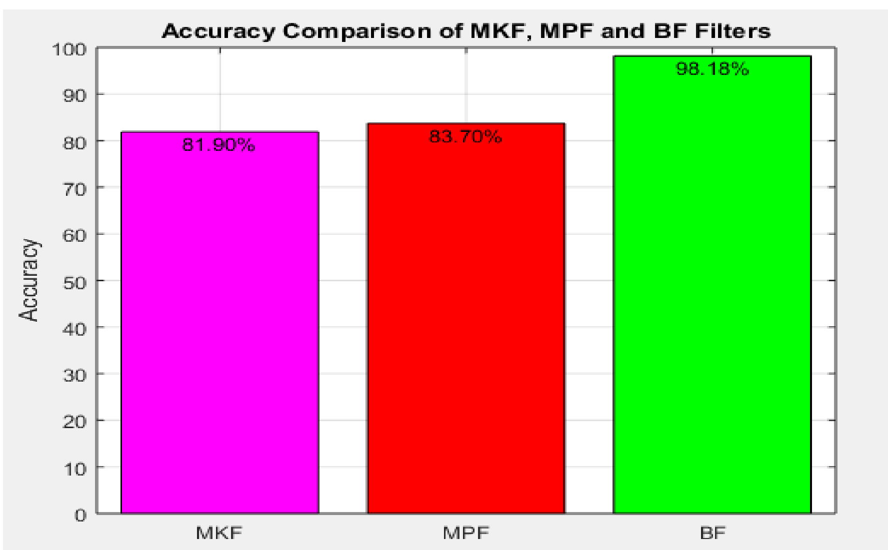

Fig 8 Comparison of Accuracy of Mean Kalman Filter, Mean particle Filter and Branching Filter

The analysis of video stream is denoted with the performance parameter Accuracy. The accuracy rate of a video is compare Branching Filter with Kalman filter, Particle filter. The detection rate of Kalman Filter, Particle Filter and Branching are 81.90%, 83.7 % and 98.18% respectively. It means branching filters are more effective as compare to other methods.

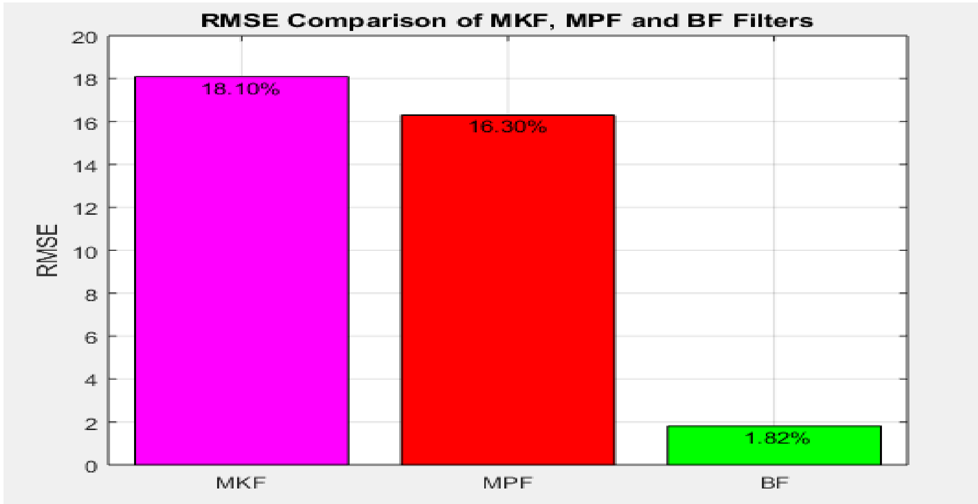

Fig 9 Comparison of Root Mean Square Error of Mean Kalman Filter, Mean particle Filter and Branching Filter.

Table 2 Comparative Analysis of Kalman Filter, Particle Filter & Branching Filter

Sr. No.	Parameter	Kalman Filter	Particle Filter	Branching Filter
1.	Detection Rate	79.75 %	82.30 %	98.52 %
2.	Accuracy	81.90 %	83.7 %	98.18 %
3.	RMSE	18.10 %	16.30 %	1.82 %

The analysis of video stream is denoted with the performance parameter RMSE. RMS error of a video is comparing Branching Filter with Kalman filter, Particle filter. RMS Error of Kalman Filter, Particle Filter and Branching are 18.10%, 16.30 % and 1.82 % respectively. It means branching filters are more effective as compare to other methods.

V. Conclusion

This study presents a novel framework to deal with three existing problems in video anomaly detection, that are the lack of labeled training data, no explicit definition of anomaly objects and the dependence on hand-crafted features. Our solution is based on filtering technique. The Branching filtering technique provide best solution to achieve max. Exactness Based upon our test and hypothetical outcomes, we proposeaccompanying: There are expanding molecule strategies that don't experienceill effects of molecule swings. There are spreading molecule strategies whose following execution and execution times can contrast most positively withconventional resampled molecule frameworks that have far reaching advance. Specialists should now think aboutCombined, Dynamic and Effective Particle branching calculations presented in this.Branching molecule channels additionally analyze positively on model determination issues and haveadditional preferred position of utilizingstandardized channel for simplicity of figuring Bayes factor.

Furthermore, our framework also has a lot of advantages over many existing systems, i.e. the nice capacities of scene segmentation, scene reconstruction, streaming detection, video analysis and model explanation.

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