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# Object Tracking in Videos Using Filtrations Technique

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**Abstract- To insure the safety of people in public as well as domestic places, surveillance cameras are being installed everywhere such as in banks, malls, markets, academic institutions, parking and most importantly on the roads where the traffic, both pedestrians as well as on wheels, is present 24x7. Different situations are captured by surveillance cameras installed at different places, like accidents on the roads are handled by cameras installed on the roads or traffic lights and crimes are handled by cameras installed in the household or streets or colonies and especially illegal activities happening in hotels or public places. The Particle Filters are suitable for object tracking in non-Gaussian environments with dynamic background thereby outperforming the conventional Kalman Filters; the third approach proposes the novel Branching Particle Filters that removes the limitations of particle filters.**

**Keywords- Accuracy, Kalman filter, Branching Filter, RMSE.**

## I. INTRODUCTION

In recent times, security and safety concerns in public places and restricted areas have increased the need for visual surveillance. Large distributed networks of many high quality cameras have been deployed and producing an enormous amount of data every second. Monitoring and processing such huge information manually are infeasible in practical applications.

As a result, it is imperative to develop autonomous systems that can identify, highlight, predict anomalous objects or events, and then help to make early interventions to prevent hazardous actions (e.g., fighting or a stranger dropping a suspicious case) or unexpected accidents (e.g., falling or a wrong movement on one-way streets). With the widespread use of surveillance cameras in public places, computer vision-based scene understanding has gained a lot of popularity amongst the CV research community.

Visual data contains rich information compared to other information sources such as GPS, mobile location, radar signals, etc. Thus, it can play a vital role in detecting/ predicting congestions, accidents and other anomalies apart from collecting statistical information about the status of road traffic.

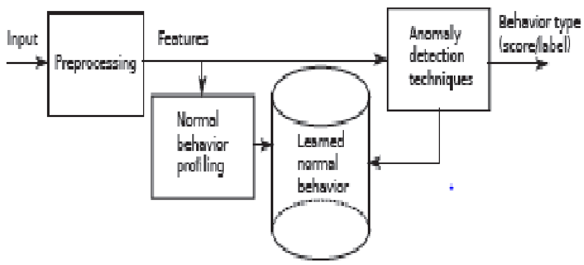


Fig 1. Overview of a typical anomaly detection scheme. Preprocessing block extracts features/data in the form of descriptors. The normal behavior is represented in abstract form in terms of rules, models, or data repository.

Specific anomaly detection techniques are used for detecting anomalies using anomaly scoring or labeling mechanism been conducted focusing on data acquisition [1], feature extraction [8], scene learning [14, 36, and 12], activity learning [15], behavioral understanding [15, 16], etc.

These studies primarily discuss on aspects such as scene analysis, video processing techniques, anomaly detection methods, vehicle detection and tracking, multi camera-based techniques and challenges, activity recognition, traffic monitoring, human behavior analysis, emergency management, event detection, etc. Anomaly detection is a sub-domain of behavior understanding [17] from surveillance scenes. Anomalies are typically aberrations of scene entities (vehicles, human or the environment) from the normal behavior.

With the availability of video feeds from public places, there has been a surge in the research outputs on video analysis and anomaly detection [15]. Typically anomaly detection methods learn the normal behavior via training. Anything deviating significantly from the normal behavior can be termed as anomalous.

Vehicle presence on walkways, sudden dispersal of people within a gathering, a person falling suddenly while walking, jaywalking, signal bypassing at a traffic junction, or U-turn of vehicles during red signals are a few examples of 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 have bit of leeway that posterity age just relies on parent not entire populace and weakness of having arbitrarily changing populaces (for example molecule numbers).

As of late, Kouritzin [10] presented 4 new class of expanding consecutive MC calculations that were intended to constrain wide molecule varieties. following and model choice execution of every one of four calculations was indicated tentatively to be better than an accumulation of prominent resample 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 have autonomy and fixed molecule quantities of numerous resample calculations so their investigation is essentially troublesome and ideal 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 resample molecule channels is one of huge 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 for remaining development of bootstrap calculation. Be that as it may, these molecule channels estimated genuine channel πn not normalized σn, don't have (a similar level of) genealogical reliance as Residual Branching channel and base their resembling choices upon (areas of the) entire populace.

Consequently, their investigation is very unique in relation to what is required for Residual 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. RELATED WORK

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 energy potentials 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 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, and thus can be separated from the regular ones. Several methods such as Chaotic Invariant [19] are based on mixture models and estimate the probability of an observation to be abnormal for anomaly detection.

Overall, all methods in the supervised approach require labor-intensive annotation process, rendering them less applicable 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 code words 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 code words. 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 Auto encoders [28] and unsupervised systems such as Convolutional Long-Short Term Memories [29], [30], [31], Convolutional Auto encoders [29], [30], [32], [33], Stacked Denoising Auto encoders [34]. By focusing on unsupervised learning methods, in what follows we will give a brief review of the unsupervised deep networks.

## III. PROPOSED WORK

The moving article is recognized by methods for movement estimation to figure situation of moving item in video plane. To recognize squares containing moving article limits by utilizing data of movement vector field. Another calculation of moving articles recognition and depiction is proposed to recognize and follow moving item in video. In light of examination of projection of 3D exhibit movement of articles, data of movement field is abused to make moving item identification increasingly effective. In this technique, foreground elements are separate out from background images and a new foreground mask is generated.

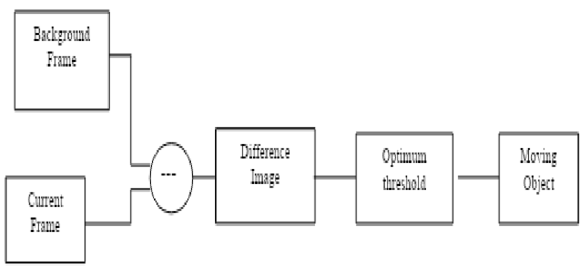


Fig 2. Foreground Extraction.

The basic application of this technique for detection of moving dynamic objects from stationary cameras. In computer vision applications, this technique is used in vast field depending upon the priority. Since the differentiation of ref. frame & current frame is observed by detection moving objects & often called "background image", or "background model".

In this system, the background subtraction & design of background model used all the images for the examination & trained them for given time period known as training time. In this time period, different plots of background, pixel Difference Image Optimum threshold Moving Object --- Background Frame Current Frame by pixel image and median is find out. In this scheme, new frames are used & each pixel values is compared with last frame value within the pixel orientation schemes. If the background model is matched with pixel value then pixel in threshold value otherwise pixel lies outside the threshold pixel value. This is known as foreground pixeled range.

## IV. RESULT ANALYSIS

In the system having dynamic model, optimal solution is estimated by particle filter for divergence state. The main feature of such system is that if there is an increment in state vector, performance of particle filter degraded. The function of Kalman filters to evaluation of all position derivate and estimation of hypothetical commitment. Since a particle filter is connected for estimation only. So, on the basis of different applications , the different filters may be used & such type of filters are particle filter and provide better output as compare to other algorithm. Another tracking methods may be used for the approximation & tracking of object.

The tracking of object is used optimal filter tracking technique.

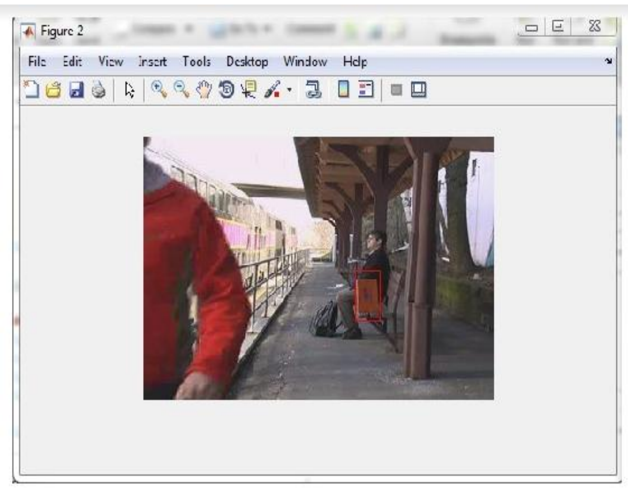


Fig 3. Objecting Tracking using Kalman Filter.

The results obtained by tracking using Kalman Filter clearly show that the position of the object does not change in the subsequent frames. Moreover, as is clear from the figure above that though people are sitting or moving around the object, but the owner as identified using SVM classifier is not present around the object for more than 45 frames. Thus the object can be declared as abandoned.

## V. CONCLUSION

The above discussion and results clearly indicate that The MSE of estimated parameter is reducing using Kalman Filter for a linear system as Gaussian noise is taken in account. It is concluded that comparative analysis of SVM based Kalman filter & Normal Filter is successful done On the other hand, complexity is reduced by Kalman filter based on SVM.

Similarly, modeling is also become so easy with SVM Kalman filter. Convenient form for online real time processing.

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