IJARSCT

International Journal of Advanced Research in Science, Communication and Technology

International Open-Access, Double-Blind, Peer-Reviewed, Refereed, Multidisciplinary Online Journal

ISSN: 2581-9429 Volume 6, Issue 2, June 2026 Impact Factor: 8.2

Advanced Video Anomaly Detection Using Artificial Intelligence Techniques

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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, Findings from the dissertation contribute to improve the performance of automated video processing system thereby improving security in areas under surveillance*

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.

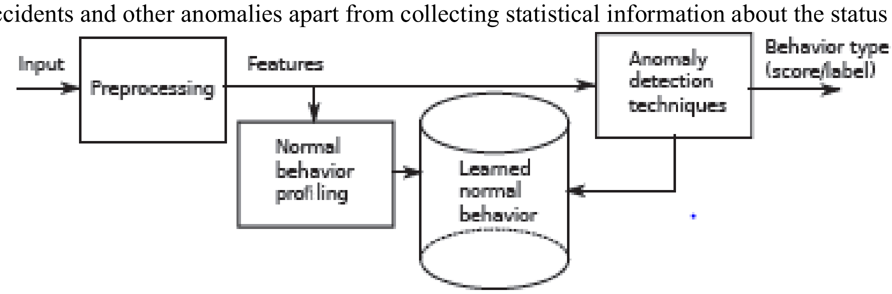

Fig.1. Overview of a typical anomaly detection scheme. Preprocessing block extracts features/data in the form of descriptors. The normal behavior is represented in abstract form in terms of rules, models, or data repository.

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, 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, a 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 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 have autonomy and fixed molecule quantities of numerous resampled 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 resampled molecule channels is one of huge leaps forward in enormous informationsuccessive 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 unnormalized σn, don't have (a similar level of) genealogical reliance as Residual 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 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

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Impact Factor: 8.2

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. discontinuities of movement vector field on limits of moving items empower us to identify moving articles obstructs in which potential limits of moving articles find. further refinement of limit of moving items and effective descriptor for moving articles are proposed also.

DOI: 10.48175/568

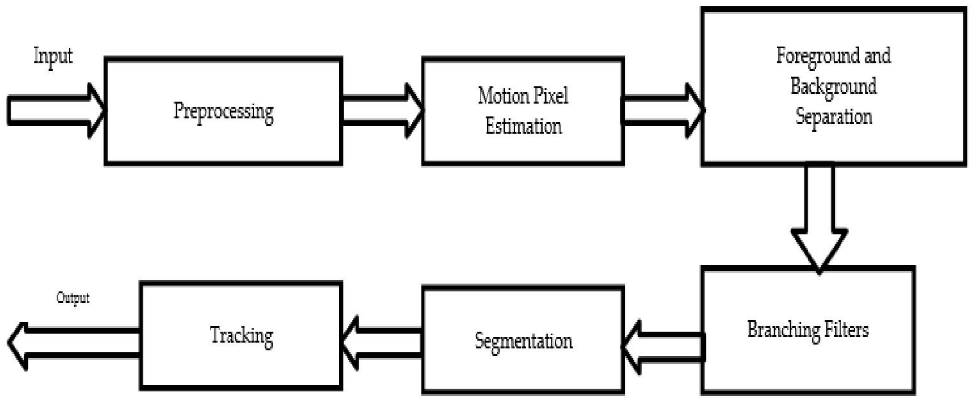

Fig 2 Proposed Methodologies

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 to grey colored image in frames.

D. Motion Pixel Estimation

Firmly identified with movement estimation is optical stream, where vectors compare to apparent development of pixels. Moving estimation careful 1:1 correspondence of pixel positions isn't necessity. Applying movement vectors to picture to integrate change to following picture is called movement pay. blend of movement estimation and movement pay is key 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, for most part with factual capacity connected over nearby or worldwide region. reason for factual capacity is to expel matches that don't relate to genuine movement. Another calculation of moving items location and portrayal is proposed to recognize and follow moving article in video. In light of investigation of projection of 3D exhibit movement of items, data of movement field is misused to make moving article identification increasingly effective. further refinement of limit of moving items and proficient descriptor for moving articles are proposed too. As perfect imaging

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model, point of view projection model is embraced in this proposed framework. Calculate first pixel value of first frame named as p1 and first pixel value of second frame and named as p2.Find mean value, add all pixel values in all frames.

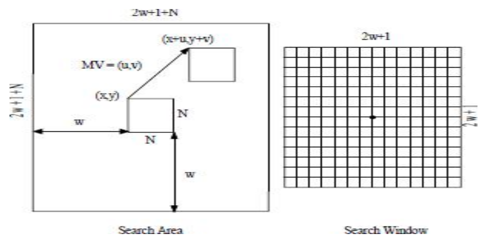

Figure 3 : Moving pixel compensation

H. Foreground and Background Separation

Foundation subtraction, otherwise called Foreground Detection, is procedure in fields of picture preparing and PC vision. Picture areas of intrigue are objects in its closer view. After phase of picture pre-preparing object localisation is required which may utilize this procedure. Method of reasoning in methodology is that of recognizing moving articles from contrast between present casing and reference outline, frequently called "foundation picture", or "foundation model". Foundation subtraction is for most part done if picture being referred to is piece of video 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 image thresholding, decrease of dark level image to parallel image. calculation contains bi-modular histogram (closer view pixel and foundation pixels), and ideal limit isolating two classes with goal that their joined spread (intra-class fluctuation) is negligible. augmentation of first strategy to staggered thresholding is Multi Otsu technique.

IV. RESULT ANALYSIS

Viable parallelization of resampled molecule channels is troublesome. These are the factors more to pick our expanding molecule channels over sampling again ones as they have solid 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 present 2 basic issues, Testing issue and limits only issues that will be utilized for correlation issue. At that point, we look at different sampling again molecule frameworks talked about above on these issues. Next, we think about most noticeably terrible of our fanning calculations to best 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 out best. For consistency, all outcomes in this are either run of mill way or normal more than 200 distinctive example ways of 100 edges of video. We decrease no. of time ventures from 500 in result down to 3.5 as result of wastefulness of other bootstrapped and other sampling molecule frameworks. We could have effectively viewed as lot bigger no. of steps in event that would just running our channels. Be that as it may, it took us weeks to get recreations we required for sampling 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.

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 propose accompanying: There are expanding molecule strategies that don't experience ill effects of molecule swings. There are spreading molecule strategies whose following execution and execution times can contrast most positively with conventional resampled molecule frameworks that have far reaching advance. Specialists should now think about Combined, Dynamic and Effective Particle branching calculations presented in this. Branching molecule channels additionally analyze positively on model determination issues and have additional preferred position of utilizing standardized 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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