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A SURVEY ON ANOMALOUS MOTION DETECTION IN VIDEO DATA

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Abstract: **The amount of data that has to be processed increases along with the demand for labor to understand the data due to substantial reduction in the cost of transmitting and storing video data. An important component of a video surveillance system is anomaly detection. Because manually analyzing and monitoring such a big amount of video would be impossible. For automated video analysis to determine typical and aberrant vehicle motion behavior for traffic management, public services, and law enforcement, automatic tracking is a crucial necessity. Even though a few anomaly detection techniques have been proposed in the past, there are still a limited number of them that can handle illumination variations, smaller object detection and tracking in poses that change, learning the movement of heterogeneous objects, anomalies in sparse and dense conditions, and tracking under occlusion that the human eye can easily detect. This survey study provides an overview of numerous techniques that have been employed to find anomalies in diverse applications.**

Keywords: **Abnormal event detection, classification, global anomaly detection, local anomaly detection, survey.**

I. INTRODUCTION

As technology becomes more readily available and affordable, the number of surveillance recordings used in both public and private facilities to ensure security and stability has expanded rapidly in recent years and will continue to do so in the near future. By replacing the ancient, manual technique of operating cameras, computer vision researchers are actively researching visual surveillance, which aims to detect, identify, and track things throughout a series of images as well as interpret and describe object behavior. A computer vision system informs the human operator to conduct a more thorough investigation of the occurrence by monitoring both immediate unlawful behavior and long-term suspect behavior. Depending on the level of human involvement, the video surveillance system can be fully automated, semi-automatic, or manual. In a manual video surveillance system, the observing individual completes each task while keeping an eye on the images being captured by the various cameras. The Surveillance system generates a large amount of data, detecting anomalous event is unfeasible for human to watch and analyze properly. Automated anomaly detection greatly reduces the amount of data that must be manually processed by excluding a significant amount of unnecessary data. These occurrences are thought to be unusual, irregular, or greatly dissimilar from others[1]. Automated scene interpretation and analysis have grown in prominence among researchers over the past ten years in the computer vision field as a result of the pervasive usage of surveillance cameras in public spaces [2]-[3]. Anything which deviates typically from normal behavior is termed as anomalous, such as sudden movement of people in a gathering, cars and bicycles among pedestrians, abnormal actions in public areas such as jumping, or fighting, a person falling suddenly while walking, A few examples of anomalies include car-following collisions, lane changes, and turning at red lights without stopping. Most video surveillance systems merely record the amount of traffic and the speed of the vehicles, not recognizing the behavior of the vehicles[4]. Although several algorithms have been created to follow, identify, and comprehend the activity of different objects in video. Anomaly Detection is sub domain of behavior understanding [5] with the availability of video from public places. Three primary types of anomalies exists. i) Point Anomaly: It is a simple type of anomaly in which the individual dataset can classified as abnormal with respect to other data. For e.g. Human Credit card detections. ii) Contextual Anomaly: For a defined context, if data is anomalous, is called as contextual anomaly. iii) Behavioral Anomaly: Any inappropriate characteristics of any instance is behavioral anomaly[6], for e.g. a video surveillance systems using CCTV cameras help to provide safety and reduce crime, by monitoring the activities of a particular area, automatically recognize abnormal behavior and gives notification to operators or users when any unexpected things happen. As the security applications are increasing, it develops need for advancement of research in area of video surveillance system[7]

Ongoing research and development in abnormal motion detection for video surveillance system has shown increase in several computer –vision based studies focusing on data acquisition[8],feature extraction[1],scene learning[9],activity learning[10], behavior learning[11] etc. These studies mainly discuss on aspects of anomaly detection methods, human behavior analysis, vehicle detection and tracking etc. The following factors explain why the problem of motion anomaly identification continues to be difficult despite recent advancements in research:

A) To identify what constitutes to be anomalous within the surveillance context and distinguish it from normal behaviour.

B) To create a scenario-independent model that can function in a variety of scene settings. To deal with the complexity in behavioral patterns of moving target.

C) To function with a reasonable level of processing complexity.

With the development of machine learning methods, computer vision-based behavior analysis, and hybrid frameworks based on deep learning. There's a lot of potential and demand for gaps in anomaly detection research. The concept of anomaly detection, often referred as outline or novelty detection, has been extensively investigated and used in a variety of fields outside of automated surveillance in the medical industry, such as marketing, network intrusions, and medical diagnostics[12]. Application areas for visual surveillance systems include security, traffic surveillance, crowd flux statistics, study of traffic congestion, individual identification, and the detection of unusual behaviour. A video surveillance system for anomaly detection can analyse human behaviour and determine if it is normal or abnormal. Any misbehavior can be prevented if suspicious behaviour is brought to the operator's attention and is further investigated. A surveillance system installed in the parking lot could examine unusual behaviors that might indicate theft.[13] This paper explores survey on detecting anomalies in traffic behavior focusing on vehicles, pedestrian and crowd anomaly detection. The review presented by author[1] is possibly the first review paper for anomaly detection techniques which covered sensors, entities, feature extraction methods, learning methods, scene modeling for detecting anomalies.

II. GENERALISED APPROACH FOR ANOMALY DETECTION

Data representing the behaviours of surveillance targets are collected by some sensors for the purpose of anomaly detection in automated surveillance processes. Following feature extraction for these data, the resulting features are fed into a modelling algorithm, which uses the learned algorithm to determine whether a state of behaviour is normal or anomalous.

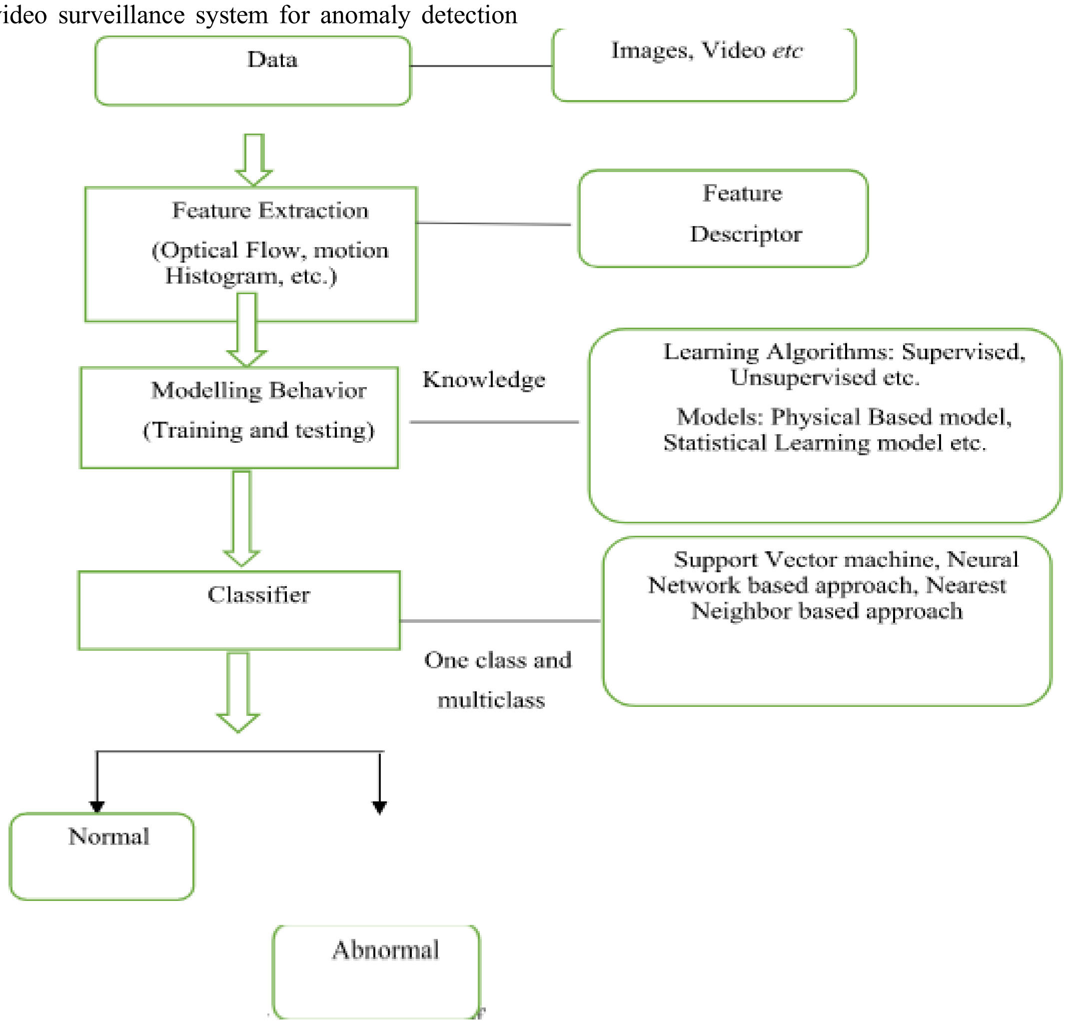

Fig 1: General Process of Anomaly Detection in Video Sequences

The flow chart in Fig1 illustrates a typical method for finding anomalies in various video sequences and datasets. The majority of the datasets on anomalies are freely accessible for research purposes and are frequently used to compare results with earlier results published elsewhere.

The issue with anomaly detection is pedestrian density because it greatly affects how they appear in videos. In videos with dense crowds, only a few areas of people's bodies can be seen, but in videos with sparse crowds, every person's entire body can be seen[14]. To find anomalies in sparse crowds, medium-density crowds, and dense crowds, many strategies are suggested. Local anomaly detection and global anomaly detection are the two categories under which studies on anomaly detection are categorized. Numerous studies on intelligent transportation systems, which include object identification, tracking, and activity analysis, have been reported [15].

III. STATE OF ART TECHNIQUES FOR ANOMALY DETECTION

Anomalies are the rare event, generally defined as outliners of the normal distribution, as an anomaly in one scene can be taken as normal event in other scene, so in training set normal patterns are learned first, these patterns are used to detect anomalies in datasets. Anomaly detection methods are mainly categorized as deep learning- and machine-learning-based detection techniques.

The two main categories for the detection of anomalous occurrences are trajectory-based analysis and motion-based analysis. The former relies on object tracking and is most effective in an open space; the latter's difficulty rises as the number of people in the scene does[34] the latter, however, is better suited for congested environments because it analyses movement patterns rather than specific objects[26] . In model based approach normal behavior of data is represented in terms of set of parameters or non- parameters.

1.1 Parametric Approach:

This approach uses Gaussian Mixture Model [34] for anomaly detection in crowded scene based on textures of optical flow in 3-D images., Regression Model [35] multi-layer- Hidden Markov Model [36] which allows analysis of scene, research paper[36] presented a frame work for modeling local spatial-temporal motion behaviors in extremely crowded scenes. In training phase, the temporal relationship between local motion patterns is captured via a distribution based HMM, in testing phase unusual events are identified as statistical deviations in video sequences of the same scene.. Author of [22] use online anomaly detection using structure analyses based on 3-D Discrete cosine transform (DCT) multi object tracker which makes tracking analysis of high density crowd situation feasible Parametric approach also uses Deep Neural Network [37][38] based method to predict anomalous event in specific region of crowd by assuming that normal data is generated through parametric distribution and probability density function. Time-efficient anomaly localization is a constant difficulty in anomaly detection since real-time scanning of video frame patches is highly unrealistic due to deep learning's processing cost. The difference between a regular occurrence and an abnormal event is frequently indeterminate under realistic conditions since the same behavior may be normal or anomalous depending on the environment; consequently, training data of normal and anomalous patterns will enhance an anomaly detection system. Author of [28]proposed When testing long untrimmed video divided into segments, fed into deep network for assigning anomaly scores for each video segment for anomaly detection, a weakly supervised learning approach using deep multiple instance learning(MIL)framework was used. This approach treated normal and anomalous video surveillance as bags and short clip in video as instance in bag.

1.2 Non-Parametric Approach:

In this method, the structure is created from the data; it has never been defined[39]. Examples of this strategy include: When segmenting outliners from big datasets (such as stochastic data) by unsupervised clustering, the Dirichlet process mixture model [40] for large-scale traffic data is demonstrated to be reliable, efficient, and mathematically elegant. Network-based Bayesian model [41] Object anomaly is the likelihood that a pixel will be associated to an anomaly p(A/D), given a detection at that pixel, if an object's velocity in the x and y directions is classified as anomalous based on the average velocity. Uo.:

$$\mathrm{Uo} = \mathrm{p}\left(\frac{\mathrm{A}}{\mathrm{D}}\right) = \frac{\mathrm{p}\left(\frac{\mathrm{D}}{\mathrm{A}}\right)\mathrm{p}(\mathrm{A})}{\mathrm{p}\left(\frac{\mathrm{D}}{\mathrm{A}}\right)\mathrm{p}(\mathrm{A}) + \mathrm{p}\left(\frac{\mathrm{D}}{\bar{\mathrm{A}}}\right)\mathrm{p}(\bar{\mathrm{A}})} \quad (1)$$

Where p (A) and p (D/A), which represent the odds of identifying an abnormality at each location on the image that remains fixed. A research paper presented in [23] to automatically adapt to changing scene dynamics and provide a model switching mechanism at each frame, a separate hidden Markov model is used to describe the sparse features during training. This model is then used to detect anomalies. An method called spatial localized limited sparse coding was presented by the author of [24] to address the issue of anomaly identification in traffic scenes. One must first evaluate the irregularity of motion orientation and magnitude and fuse it using a Bayesian model in order to manage more varieties of abnormal occurrences. Anomaly detection relies heavily on feature representation since it is crucial to extract pertinent features from input video. The author of [29] combined histograms of directed gradients and swimming acceleration to aid in learning. During the learning stage, the research work given in [30] introduces the histogram of optical flow orientation, magnitude, and entropy (HOFME) descriptor. In testing, HOFME feature vectors were extracted to create a normal pattern, and a closest neighbor search was used to identify abnormal events.

1.3 Reconstruction Methods

Based on deep learning have been utilized extensively for object detection and behavior understanding. Anomaly detection generally based on the basis of faults in reconstruction of the input data provided with assumption that normal data can be insert into lower dimensional subspace for normal and abnormal classification some examples are sparse coding[16][17][18]auto encoder[19] and principal component analysis[20] based approach. These models are all susceptible to background complexity. As these methods mostly rely on reconstruction errors of the full frame to find anomalies. Convolutional Auto-Encoder(CAE) based anomaly detection approach by[21] that captures temporal information using Long short-term memory networks(LSTM) and ability to handle complicated backdrop and even tiny region anomalies using a method based on generative adversarial networks (GAN).The use of moving camera tends to increase due to popularization of robots, cars and drones which are moving platforms that performs surveillance of large areas using large sensors to solve the problem of video surveillance using moving camera author of [25] proposed method which represent the video data as a low rank projection on a union of subspaces plus a sparse residue term, by taking advantage of the intrinsic structure of used sparse decomposition without requiring previous data synchronization to detect anomalies, this method is robust to video with cluttered backgrounds

IV. CLASSIFICATION TECHNIQUES FOR ANOMALY DETECTION

The classification-based methodology for finding anomalies can be thought of as a supervised and semi-supervised method, where first, the classifier is trained. using the training dataset and then depending on the test case, the dataset is categorized as normal or anomalous using the learnt output. The two subcategories of this technique are one-class and multi-class. While multi-class techniques require that training data contain labelled instances of both normal and anomalous classes. Class-based anomaly detection techniques assume that all training data have a single label and in order to create a boundary, support vectors are used.

Following sections explore different kinds of classification algorithm in anomaly detection technique.

1.4 Support Vector Machine based Technique

Support vector machine for classification or regression was first proposed by Vapnik and Lerner [42]. It can be used in one class settling in visual surveillance. Research paper[30] used SVM for anomaly detection as this method generally exhibit good performance and fast to run. Compared to other machine learning techniques, they are more dependable and can handle enormous datasets. also maintains anomaly detection in congested scenes and resistance to local noise. A robustness to local noise and the ability to detect anomalies in busy environments is also maintained by OCSVM based anomaly detection in which HOSA and HOGs features were extracted over image patches. Author of [32] uses Support Vector Data Descriptor method as it is known as best suited for outliner detection. Research paper presented by [43] uses one class SVM method through the entire video-based traffic monitoring process which include the gathering of video data and the classification of trajectories, for the detection of abnormalities .Overall accuracy achieved by this system is about 94% when data set of large variations were used. Author of[44] proposed a method for abnormal event detection that is based on deep features extracted with pre-trained convolutional neural network, then CNN features are fed into one class Support Vector Machine classifier to learn normality from training frames. Let $X=\{x1, x2, x3 \ldots\ldots, xn/xi \in \mathbb{R}n\}$ denote the set of training frames, By setting the regularization parameter to 0.2, the SVM model will learn a separate region from feature space for capturing normal frames, which means the model will have to distinguish between 80% of training frames as normal and the remaining 20% as outliners. This method produces an overall frame-level AUC of 97.1% when tested over the AVENUE and UMN datasets, however since there is a shift in lighting when individuals move around, the drawback is that it doesn't quickly notice aberrant events. So possible approach to overcome this limitation is to extract motion and appearance information using convolutional two-stream networks[45]. For anomaly judgement, the intra-frame classification strategy proposed in research paper [27] evaluate the probabilistic output of anomalies through a multi-class SVM classifier. This makes detection faster and more accurate by using this classifier blocks inside the frame.

1.5 Neural Networks Based Technique

Both one-class and multi-class scenarios can use neural network-based anomaly detection. The operation of multi-class settings involves two steps: first, it trains a neural network to learn about normal classes using normal training data; second, it incorporates each test instance into the network to determine whether the network is accepted as normal and vice versa[46][47]. Bayesian networks can be used for anomaly detection in multiclass settling. Different types of neural network techniques for anomaly detection have been proposed such as Fast region based –CNN(Fast R-CNN) that uses a high variation deep neural network that works effectively in object classification over conventional CNN for anomaly detection[48].As detection of abnormal motion in crowd is extremely challenging due to severe inter- object occlusions, varying crowd density and complex mechanics of crowd, author[49] proposed spatial-temporal Convolutional neural network(CNN) to ensure robustness to local noise, increasing detection accuracy, to access both single and complex motion information from continuous frame. Once the crowd is moving, the motion patterns and texture of the crowd can be captured using spatial-temporal CNN, which is obtained by convolving a 3-D kernel to spatial-temporal volume. This method can act immediately on raw inputs without any preprocessing for hand-crafted features. Four datasets, namely USCD, UMN, SUBWAY, and U-Turn, with varying degrees of abnormality, were compared in order to assess the usefulness of this method. This method performed well in terms of identifying aberrant motion.

1.6 Clustering Techniques for anomaly detection

The methodology of clustering-based techniques holds that regular occurrences predominate and show up frequently in datasets. Author[31]suggested a trajectory clustering method that takes the distance between trajectory points into account and allows various clusters to contain elements of the same trajectory (sub trajectory). This method can identify cars moving in the wrong way, but it cannot differentiate between many forms of abnormal behavior, such as going rapidly or slowly, or deviant action (such as fighting). The trajectory-based clustering method can identify unusual occurrences connected to the migration of people all around. However, it is impossible to distinguish between local aberrant activities like leaping the payment gate and worldwide human migration.. A unified framework that combines the results of trajectory analysis with pixel-based analysis was proposed by the author of[33] to get around this limitation of the trajectory-based clustering method. This framework can detect abnormal behavior related to speed and direction as well as complex behavior related to finer motion of each object. improving histogram discrimination. By measuring the distance between the pair-wise BoW histograms of each action instance, Bhattacharyya, Chi-Square, and Euclidean distance have been utilized to define a similarity matrix. (Hm).

$$D_H^{Bhat}(H_1,H2)=\sum\sqrt{H_1(b).H_2(b)} \quad (2)$$

$$D_H^{Chi}(H_1,H2)=\frac{1}{2}\sum(\frac{(H_1(b)-H_2(b))^2}{H_1(b)+H_2(b)} \quad (3)$$

$$D_H^{Euc}(H_1,H2)=\sum\sqrt{\left(H_1(b)-H_2(b)\right)^2} \quad (4)$$

Euclidean distance ($D_H^{Euc}(H_1, H_2)$) is empirically selected to measure the similarity among histograms. Similarity among histogram is defined as follows:

$$Sim(H_1,H_2) = -D_H^{Euc}(H_1,H_2) \quad (5)$$

Using, this similarity matrix, affinity propagation algorithm is employed to cluster finer motion of each individual.

V. CONCLUSION AND SCOPE FOR FUTURE

The author[30] exploited swarm intelligence to extract motion characteristics from appearance features for the difficult problem of anomaly motion detection. The suggested technique is computationally efficient and works well for crowd analysis with occlusion, local noise, and local scale fluctuations. Due to a lack of sufficient training data sets, this technique has some false detection limitations when applied to the UMN dataset. Author[22] proposed a structural context descriptor for describing individuals in crowds. This algorithm was only tested in visible video sequences with RGB channels; it has difficulties in adverse weather conditions, such as foggy or rainy days. These limitations can be overcome by using multi spectral clues with properties other than the traditional visible spectrum. Using a variety of sparse decomposition-based algorithms, research paper [26] employed this technique to find anomalies in video sequences. Author[50] presented a group aggregation descriptor for analysing crowd aggregation using the KLT tracker, however testing findings revealed a larger dependence on parameter settling, making it difficult for the algorithm to construct a fully autonomous system. It also faces numerous difficulties because it is difficult to find a single feature extraction technique that works equally well for all target kinds. Since each approach has only one use and may fail when subjected to the variety of targets and behaviour prevalent in realistic circumstances, there aren't many methods that can be applied to a wide range of targets for automated anomaly detection solutions. The area of individual/crowd monitoring is where this absence of cross-target research is most critical. Consequently, additional research is required to examine the applicability of approaches to a larger range.

Unsupervised or unstructured strategies seek to tackle more difficult problems but would be more practically practicable. In general, supervised and unsupervised techniques are likely to yield good anomaly detection performance, although the demand for data annotation may not always be practical. We think there is a great deal of potential for advancement, particularly for data collected in real-world scenarios with complicated human and traffic behavior in the presence of numerous noise sources.

Most anomaly detection research for automated surveillance has taken into account fields of vision that span from roughly the size of a room (10 m) to the size of a medium-sized parking lot (100 m). There is a dearth of study that takes into account the extremes of field of vision, such as those found in a satellite image or a portrait of a human face. Due to the availability of these datasets from the surveillance cameras installed in various locations, researchers have created a variety of anomaly datasets. The majority of anomaly datasets are openly accessible for academic research and are frequently used to compare findings to earlier findings that have been published elsewhere. Despite being straightforward and subject to numerous restrictions, only a few number of datasets are extensively utilized. Therefore, understanding various anomalous video data sets is necessary for research.

Many of the anomaly detection models that are currently available require too much computer power for real-time inference in realistic situations. Consequently, there is a constant need to create inference methods that are computationally manageable.

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