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Unusual Activity Detection in Surveillance Video Scene: Review

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ABSTRACT

Abnormal activity may indicate threats and risks to others. An anomaly can be defined as something that deviates from what is expected, common, or normal. Because it is difficult to continuously monitor public spaces, intelligent video surveillance is necessary, which can monitor human actions in real-time and categorize them as ordinary or exceptional, as well as create an alarm. Human activities in public and sensitive regions such as bus stations, airports, railway stations, malls, banks, universities, car parks, roads, and other regions can be monitored using visual surveillance to prevent crime, theft, terrorism, vandalism, accidents, and other suspicious activities. This makes video surveillance a key to increasing public security. The main objective of event discovery is to discover the occurrence of events and categorize them into normal or abnormal actions. This discovery requires identifying and tracking objects and then learning what is going around those tracked objects. Recent research is based on one of two technologies: handcrafted features and deep learning models. Handmade features are based on extracting low-level features, and their strength is based on selecting the best features, that produce the best results. After the success of deep learning techniques for classifying images, the researchers examined the ability of deep learning techniques to detect, which bypasses the manual step of feature extraction and works directly with images. This paper presents a survey of both handmade and deep learning models to detect abnormal events.

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1. Introduction

Video surveillance is a critical component of enhancing public safety. The primary purpose of event detection is to identify the occurrence of events and classify them as normal or abnormal. In general, as shown in Figure (1) the unusual activity detection system consists of the following main stages: segmentation of the scene into frames, background extraction, foreground extraction, motion detection, and activity classification into normal or abnormal activity [1]. To do so, we must first recognize what is going on in the vicinity of the monitored objects. It is necessary to take action to determine whether an event is normal or aberrant. Abnormal behavior may indicate threats and risks to others. Finding such anomalies in videos is critical for a variety of applications ranging from automatic quality control to visual monitoring settings such as jails and schools, as well as banning inappropriate violence in

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children's movies. The majority of work in event analysis is centered on two primary paths [2]: the first is video sequence walking or jogging, and the other is anomalous detection, which focuses on recognizing rare or unexpected events such as violent behaviors. Local anomalous detection and global anomalous detection are two types of anomalous detection [3].

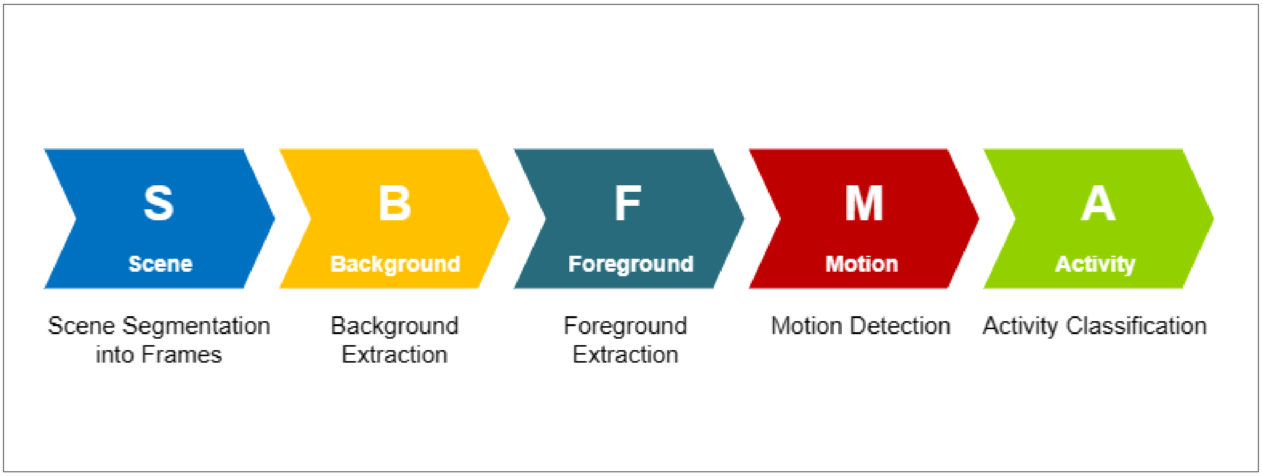

Fig1 - The block diagram of the main stages of the unusual activity detection system [1].

A local anomaly is a person's behavior, such as driving in the other direction. Global anomalous, on the other hand, refers to the behavior of a group of people, such as when most people run in opposite directions. Several methods for detecting human activity in a situation have been proposed [4]. As illustrated in Figure (2), there are two primary types of techniques that may recognize normal and abnormal occurrences in crowded and uncrowded situations. The first is a handcrafted features-based technique, which relies on extracting a collection of features such as motion or texture, making it more suitable for cluttered scenes. The other is a deep learning-based strategy that relies on tracking objects of interest to generate a trajectory, with any trajectory that differs from previously learned trajectories being considered abnormal. It is not known how deep learning-based strategies work because it's a black box. It will be difficult to debug if you run into a problem. The handcrafted feature-based techniques rely on selecting the best characteristics that are appropriate for crowded or uncrowded environments. However, the vast range of actions in traditional techniques is its principal impediment [5] [6]. The rest of this paper is laid out as follows. Section 2 discusses the related works and methodologies. The classification Techniques focus mostly on recognizing human action in section 3. Finally, in section Four there is a conclusion.

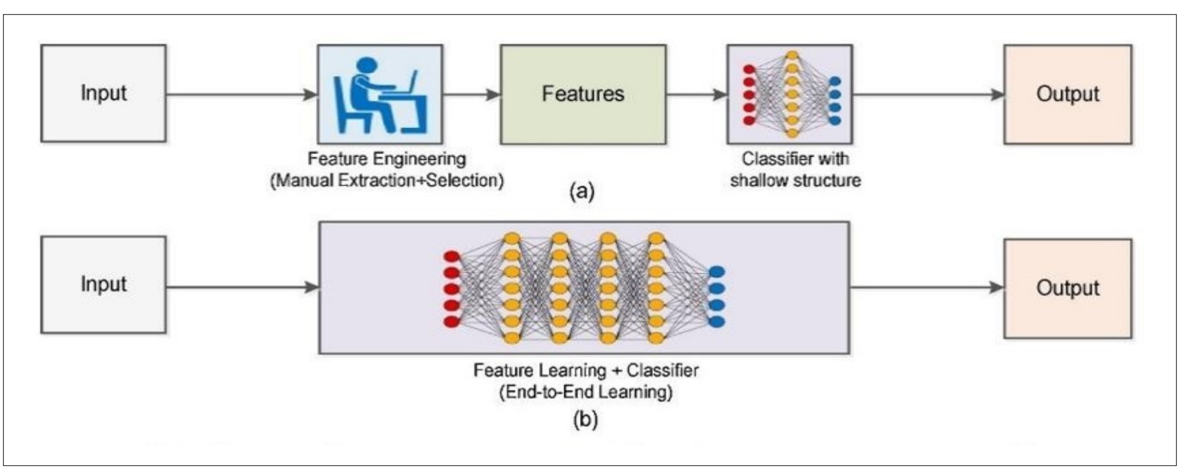

Fig.2 - a. Model-based on Handcrafted features, b. Model-based on deep learning [7].

2. Related Works

There are now several studies looking into abnormal event detection, intending to detect anomalous occurrences and categorize them into local or global behaviors. Handcrafted features-based models and deep learning models are the two primary types of recent research. The public datasets used for anomalous detection can be divided into two categories based on the content of the videos: violence datasets and interaction datasets [8-11]. Videos of violent acts are included in the violence datasets. The movie-fight dataset and Hockey-fight dataset are two of the most well-known violence datasets. The first dataset consists of 200 action movie clips shot in a range of scenes and at various resolutions. The other dataset contains 1000 action clips that have been classified as fights or non-fights. Videos showing anomalous interaction between groups of individuals are included in interaction datasets. The most popular interaction datasets are: I) The UCSD dataset, which contains 78 video clips divided into two subgroups. Video clips of pedestrian walk occurrences, both normal and atypical, for training and testing. Anomaly caused by non-pedestrian entities in the pathways or aberrant pedestrian motion patterns. II) The Avenue dataset contains a total of 30652 frames in 37 video clips for training and testing. III) The Subway dataset contains movies of several forms of anomalous incidents in a total of 64902 frames [12-14].

2.1 Handcrafted Based Models

Every day, we educate a toddler on how to recognize diverse items using feature learning approaches. The extraction of features in the Spatio-temporal domain is fundamental to the technique based on handcrafted features. A bag-of-words is a collection of low-level features that can be employed in both supervised and unsupervised learning situations. Its effectiveness is determined by how well the features are chosen. The classification is then done using a machine learning classifier that has been trained. Deepak et al [15] detect and distinguish aggressive actions in crowded scenes. To extract motion information from video frames, Spatio-temporal autocorrelation of gradient was used as a feature extraction method. It identifies local correlations between space-time gradients and feeds them into an SVM classifier for recognizing violent and nonviolent actions. The algorithm was tested on two standard datasets for violence detection: the crowd violence dataset and the hockey fight dataset. The recognition rate for their proposed methodology was 91.3 percent for the "crowd violence data set" and 90.4 percent for the "hockey fight data set". In complicated surveillance situations, Yang et al [16] detect abnormal vehicle behavior. They identify abnormal behavior by breaking down complex global behaviors into their spatiotemporal properties. Learning behavioral spatiotemporal context is required for the suggested cascaded topic model methodology. It identifies local behavioral patterns by using MRF-LDA (Markov random fields - latent Dirichlet allocation) to model the relationship between multiple trajectory segments of the same moving object and then using the spectral clustering algorithm to cluster local behavioral patterns topics into categories. After that, the LDA topic model was used to learn the temporal context of global behavior. The abnormal behavior recognition method was developed based on the learned Spatio-temporal context of behaviors but in a top-down strategy. It firstly detects abnormal video clips by training LDA topic models independently for each type of non-overlapping video clips that checked for abnormal behavior. An abnormality scoring function (abf) is calculated depending on the likelihood value of anomalous behavior in the video clip if (abf) is lower than a threshold value the video clip is considered to contain an abnormal behavior. Once an odd video clip has been identified, local behavior subject categories are selected, and anomalous moving item trajectories are located. The researchers compared the performance of the cascaded topic model methodology with two different methods: a single layer “LDA model” and a two-level hierarchal “Cas-LDA model” on the QMUL Street Intersection Dataset. This resulted in the researchers exploring other techniques to have better detection. Das and Mishra [17] detect unusual trajectory in crowded scenes by clustering trajectories based on several independent features (shape, density, standard deviation, and mean position) to locate the anomalous behavior, as an unusual trajectory may resemble a normal pattern in one aspect but differ significantly in others. They use the Shannon entropy to classify anomalous trajectories, with anomalous trajectories having higher levels of entropy than conventional trajectories. As a result, the probability distribution's entropy is evaluated, and if it exceeds a certain threshold, it is labeled as anomalous. The approach was tested on two datasets, the crowded scenes dataset, and the UCF crowd dataset, with a detection rate of 98 percent. Local aberrant behavior, such as walking in the incorrect direction in a busy situation, is detected by Zhu et al. [18]. Based on the concept of optical flow energy, deviant behavior has higher energy than normal behavior. They represent the behavior of the entire video sequence using a histogram of optical flow feature categories taken from the image. Then, if the log-likelihood estimated using a mixed naive Bayes model is less than a predetermined threshold value, consider local behavior as unusual. The methodology was compared to three techniques: a mixed dynamic texture-based technique, a social force-based technique, and a technique based on adaptive optical flow filtering. These methods were tested on two data sets: the subway dataset and, the UCSD dataset with the findings showing that they outperformed the other three ways in detecting fast anomalous behavior while skipping the slow. When compared to deep learning models, the handcrafted features-based approach is exceptional since the amount of training data is not a factor. The ability to view and analyze features to select the best features also contributes significantly to the results. However, the fundamental impediment is the large range of trajectories in previous techniques.

2.2 Deep Learning-Based Models

Following the success of deep learning algorithms in image categorization, researchers have looked into their potential to detect anomalies. Deep learning techniques do not require human intervention because they bypass the manual feature extraction process and deal directly with raw data. The quantity of learning is determined by the data quality, which has an impact on the quality of the final product. The performance of a system will be harmed if the data quality is poor [19-21]. To develop an end-to-end deep video anomaly detection system, Pang et al. [22] presented a self-training deep neural network. Initial detection was done to obtain anomaly scores, which were then used to divide the frames of unlabeled films into the anomaly and normal sets. To maximize the anomaly scores, these sets were utilized to train a ResNet-50 model and a fully connected network. Then, by re-computing the anomaly scores of all frames, a self-training method was utilized to enhance the anomaly score, resulting in better anomaly scores than the initial anomaly scores. Three benchmark datasets were used to test the approach: subway, UCSD, and UMN. In surveillance systems, there are two sorts of anomalies. I) Visual anomaly of things that are visually distinct from regular ones, which necessitates the identification of odd data samples. II) A motion anomaly is when an object with a typical look moves oddly. By constructing a semi-supervised deep support vector data descriptor, Ruff et al [23] suggested an end-to-end deep technique for appearance anomaly identification in photos. They extended data boundaries in a way that allows for the discovery of anomalous samples. The suggested model, which was trained on the MNIST and CIFAR-10 datasets, which provide a solid baseline by extracting distinct features, aids in improving the outcomes. The proposed technique's performance was compared to that of state-of-the-art approaches, and it was found to be on par with other detection techniques.

Because of their multilayer nature, end-to-end deep learning is a dark box, and its predictions are difficult to trace by humans. It will be tough to solve a problem if it is used as a counter. As a result, the researchers are attempting to combine deep learning with standard approaches [24-26].

Anitha and Arun [27] proposed an unsupervised deep learning technique for video anomaly detection that is unsupervised during both training and testing. The spatial feature is made up of original frames and edge frames from an unlabeled video that is fed into the deep learning model. Convolutional autoencoder and convolutional LSTM are used in the deep learning model to learn both spatial and temporal features, with reconstructed frames as output. The reconstruction error determined from the Euclidean distance between the original frame and the rebuilt frame recognized an abnormal occurrence. Two benchmark datasets were used to assess methodology: UCSD and avenue. In the avenue dataset, it scores 90.7 percent accuracy, whereas, in the UCSD datasets, it reaches 98.4 percent accuracy. Kamoona et al [28] discover anomaly events in real-world surveillance footage (3D convolution features). Then, using nave Bayes for classification. The probability of the normal class has been calculated only after changing it based on normal video bags sparsity estimation, and regard those less than user-defined threshold as abnormal. They compare the methodology's performance to that of the standard nave Bayes technique, passion nave Bayes technique, and BOVW+SVM using the UCF dataset, which is real-world surveillance footage. Their technique, combined with BOVW+SVM, yielded a high close performance, but the passion nave Bayes yielded the lowest.

3. Classification

The approaches described can be divided into two groups. I) supervised models, as illustrated in table 1, that were trained on labeled data to improve precision. II) Unsupervised models, as demonstrated in table 2, do not require labeled data because the model attempts to extract patterns on its own. Various classifiers have been employed in both supervised and unsupervised settings. According to the papers reviewed, SVM was the most widely used supervised classifier [15] [29] [30], whereas CNN was the most widely used unsupervised classifier [31] [22] [24]. Anomaly representation has been applied in both categories using distinct features. Features are categorized into: I) Appearance information [4] [20] [27]. II) Motion information [19] [32] [33]. III) Both appearance and motion information [34] [35] [28].

Table 1 shows the results of supervised anomaly detection.

Model	Method	Scene
Models based on handcrafted features	Detecting violence based on autocorrelation of gradients [15]	Crowded scenes
	Detection of local abnormal behavior based on the optical flow [18]	Crowded scenes
	Detection of global abnormal events based on the optical flow covariance matrix [19]	Crowded scenes
	Detection of an abnormal event based on contextual information using a directed gradient histogram [20]	Crowded Scene
	Detection of abnormal events based on appearance and movement information [21]	Crowded scenes
	Detecting violence based on the Weber motion Local Descriptor [29]	Crowded scenes
	Detecting violence based on Spatial-temporal point of interest [30]	Crowded and uncrowded scenes
	Anomaly detection based on a spatially positioned optical flow descriptor histogram [32]	Crowded scenes
Models based on deep learning	Detection of abnormal events based on generative adversarial networks [36]	Crowded scenes
	Detection of abnormal events based on a deep single class convolutional neural network [33]	Crowded scenes
	Anomaly detection based on a variable Gaussian mixture autoencoder [35]	Crowded scenes
	Anomaly detection based on scattered information of deep C3D features [28]	Uncrowded scenes

Table 2: shows the results of unsupervised anomaly detection

Model	Method	Scene
Models based on handcrafted features	Detection of local and global aberrations by the hierarchical representation of features and Gaussian process regression [4]	Crowded and uncrowded scenes
	Detecting abnormal behaviors in complex scenes based on spatial-temporal context [16]	Street Intersection scenes
	Abnormal pathways detection using a multi-object tracker based on multiple independent features [17]	Crowded scenes
	Localization and detection of abnormal behaviors based on optical flow and histogram-based descriptor [34]	Crowded scenes
Models based on deep learning	Detection of abnormal events based on learning the combined representation [31]	Crowded scenes
	Deep predictive coding network for anomaly detection [37]	Crowded scenes
	End-to-end neural network detection of anomalies [22]	Crowded scenes
	Detecting local anomalies by combining semantic information with optical flow [24]	Crowded scenes
	The detection of anomalies using a hybrid deep learning architecture [27]	Crowded scenes

Many scientists have sought to develop systems that can analyze and comprehend people's behavior. Researchers previously concentrated on supervised learning techniques for classifying various human behaviors. If unexpected occurrences are well-defined and enough training samples are available, fully supervised model-based techniques are appropriate [38]. The majority of works on abnormal behavior detection have used a supervised learning method, based on the assumption that both normal and abnormal behavior have well-defined classes. In the supervised method, a training set of anomalous and normal behavior would be used to build a model, which would then be used to identify new behavior sequences as normal or abnormal. When there are few examples of anomalous conduct, this strategy is ineffective. The majority of research on detecting aberrant activity in surveillance video relies on supervised learning because it has a high level of accuracy [39].
The unsupervised learning approach is based on the idea that aberrant events happen less frequently than regular events. The unsupervised method creates a predictive model of normal or often occurring behavior patterns, then utilizes the model to identify behavior sequences as abnormal when they are completely different from the normal. Although some of the work employs ensembles of classifiers, the majority of current research has focused on abnormal detection algorithms that employ incremental clustering. These methods function by comparing a new pattern to a set of clusters that represent historically usual behavior and identifying the new pattern as anomalous if its distance from the closest cluster is greater than a certain threshold [40].

4. Conclusions

A survey of state-of-the-art anomalous detection approaches is presented in this review, which includes both handcrafted and deep learning-based approaches. Many steps are involved in abnormal detection methods (pre-processing, feature extraction, classification, decision making). Each step is in charge of a specific action that will have an impact on the overall system's outcomes. Handcrafted feature-based approaches allow you to train your model on a variety of classifiers. They also recognize and choose the optimal feature to extract that would yield accurate results, but the key challenge is the large range of trajectories in older procedures. Although pure deep learning is better for real-time anomaly detection, it may not produce as good of results as other techniques. Because of their layered structure, deep learning is a black box. We can't explain how a model works, and if it solves an issue, it will be tough to troubleshoot. The use of both handmade features and feature learning to create a solid baseline by extracting more distinct features not only improves the outcomes but also solves the problem of not having a precise description of abnormal events. The amount of learning is determined by the data quality; if the data quantity and quality are insufficient, performance will suffer. So far, researchers have been attempting to improve anomalous detection by experimenting with various tweaks to each strategy handcrafted, pure deep learning, or a combination of both approaches to achieve the best results.

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