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Detection of Anomalous Action While Capturing and Classification using Enhanced SVM Technique

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Abstract: **It is now popular to develop video surveillance systems to enhance the security of our daily life. Recently increasing concern over security problem of everywhere people assembling. The video surveillance a smart way of providing security in the place such as public areas, airports, railway stations, parking lots, and industrial plants are monitored by operators. At present, the surveillance systems have turned to automatically identify the anomalous action from video streams. The aim of this paper is to detect abnormal events in video streams, a challenging but important subject in video surveillance. We propose an automatic abnormal object detection and classification model for video surveillance. The model of surveillance system carried out by two steps. The first steps for segmenting object from background and connected component and seconds steps for classification whether the objects are cause of abnormal events. The classifier system, support vector machine (SVM) is trained with features extracted from object's optical flow descriptor to classify abnormal objects from normal one. The features provided in training and testing of classifier is histogram optical flow descriptor that describes objects in video frame movements efficiently.**

Keywords: Abnormal Events, Anomaly detection, objects detection, background subtraction, optical flow, HOFO, Multiclass SVM.

I INTRODUCTION

Visual surveillance is currently one of the active research topics in computer vision. The increasing Concern about public safety and law enforcement has caused a great deal of growth in the number of surveillance cameras. In video surveillance motion detection could take a vital role for security and safety in public places such as concerts, sporting events, parking places, town canter's, political events, etc. The detection of abnormal motion would benefit from a system capable of recognizing perilous and inconsistent conditions and circumstances to make the system operators fully aware and attentive. Abnormal event detection, the general approach of these works consists of modelling normal behaviours, and then estimating the abnormal behaviour or attitudes between the normal behaviour model and the observed behaviours. Finally the variations are labelled as abnormal. The principle of the general approach is to exploit the fact that data of normal behaviours are generally available, and data of abnormal behaviours are ordinarily unavailable. For this reason, the deviations from examples of normal behaviour are used to characterize abnormality. We will estimate the variations of motions to discriminate potential abnormal motions without mentioning any restriction on the number of people or moving objects.

The rest of this paper is organized as follows: Section 2 describes the related work; Section 3 is devoted to the presentation of the proposed approach; Section 4 introduces the experimental results; and finally, Section 5 concludes and indicates future work.

II RELATEDWORKS

Authors in [1] proposed a visual monitoring system that passively observes moving objects in a site and learns patterns activity from those observations, detect of unusual events in the site that do not fit common patterns using a hierarchical classification. Also, authors in [2] address the problem of detecting irregularities in visual data as a process of constructing a puzzle: regions in the observed data which can be composed using large contiguous chunks of data from the database are considered very likely, whereas regions in the observed data

which cannot be composed from the database are regarded as suspicious.

In [3], it was noted that behaviour recognition publications in the past three years are three times as many as found in all of the related publications. Video surveillance, which involves acquiring and processing visual data from a scene, to detect target(s) along time and space for purpose of recognizing interesting situations and perhaps generate alarms, has been a particularly hot topic.

It typically begins with change detection and motion information capture for moving targets (using tracking or non-tracking methods), to enable successive high-level event analysis. Low level motion features could also be used for abnormal event detection. An algorithm based on collecting low-level statistics is presented in [4]. In [5], an algorithm focuses on single action with one person, such as hand-waving, boxing et al. These methods base on the partial information, such as in small observation windows of the image, they do not get the monolithic information of the frame.

III PROPOSED WORK

We proposed a model which is based on optical flow features to categorize patterns of human behaviours and activities followed by some geometrical treatments to detect abnormal motion in video. The moving objects in a frame have velocity of displacement known as motion vectors are determined by optical flow estimation. The each pixel having motion field u and v further summarized with histogram of optical feature (HOF) with losing discrimination of normal and abnormal action of objects and followed by classification support vector machine (SVM) is carried out to separate abnormal events.

The block diagram shown in figure has the proposed model of architecture of abnormal object detection for surveillance videos. The model has two kind of block process the first is training process and other is testing block process.

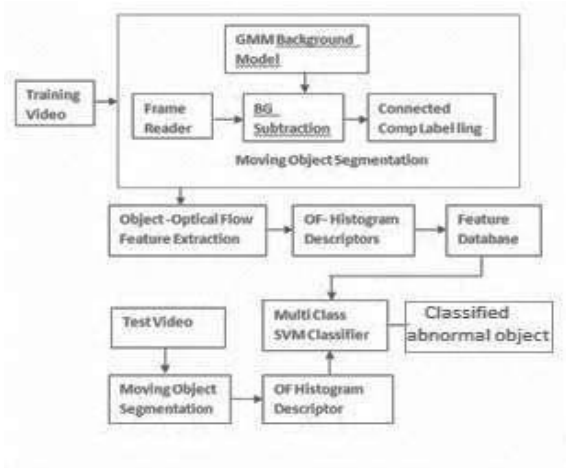


Figure 1 Block Diagram of Proposed Model

Normal or abnormal events are not punctual, but they occur during some number of successive frames. The abnormal events can be considered as false alarms if they just appear few frames intermittently in the long normal sequence, which can be adjusted to ’normal’. The results are post-processed by presenting a threshold % on the number of detected frames. If negative predicted results (abnormal states) continue beyond the threshold in positive results (normal states) stream, then change the state from ’normal’ to ’abnormal’.

On training process, the input frame read from videos is segmented into moving objects using background subtraction model and connected component techniques. The each object’s moving velocity vector estimated from optical flow model and then optical flow field (vector) is converted into optical descriptor using histogram bins represented by optical vector orientation. The feature descriptor of each object is stored in database is known as feature database for training SVM classifier.

A.Background Subtraction

In this scenario the main challenge is to detect objects in convenient time interval without using any special hardware specifications in image processing and consuming a lot resources for development of this detection mechanism efficiently.

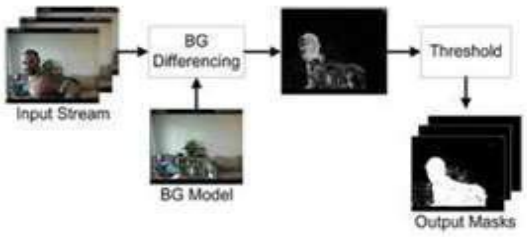


Figure 2 Background subtraction process for object categorization

The above figure show efficient process for object categorization in real time video streaming. In this process input as streams in video generation and differentiating each video frame with constitute process on object and then finding threshold for tracking objects in real time formation of human moving in processing states. When a new image is captured, the difference between the image and background model is computed for moving object detection. In MOG, the background isn't a frame of values. Rather, the background model is parametric. Each pixel location is represented by a number (or mixture) of Gaussian functions that sum together to form a probability distribution function F,

) =

The mean *u* of each Gaussian function can be thought of as an educated guess of the pixel value in the next frame.

We assume here that pixels are usually background. The weight and standard deviations of each component are measures of our confidence in that guess (higher weight & lower σ = higher confidence). There are typically 3 Gaussian components per pixel. To determine if a pixel is part of the background, we compare it to the Gaussian components tracking it. If the pixel value is within a scaling factor of a background component's standard deviation σ, it is considered part of the background. Otherwise, it's foreground.

B.*Connected Components*

The method described above allows us to identify foreground pixels in each new frame while updating the description of each pixel's process. These labelled foreground pixels can then be segmented into regions by a two-pass, connected components algorithm. Because this procedure is effective in determining the whole moving object, moving regions can be characterized not only by their position, but size, moments, and other shape information. Not only can these characteristics be useful for later processing and classification.

C.*Optical Flow*

Optical flow is the distribution of apparent velocities of movement of brightness patterns in an image. It can give important information about the spatial arrangement of the objects and the change rate of this arrangement. B.Horn and B. Schunck proposed the algorithm introducing a global constraint of smoothness to compute optical flow. The basic Horn-Schunck (HS) optical method is used in our work. The HS method combines a data term that assumes constancy of some image property with a spatial term that models how the flow is expected to vary across the image. For two-dimensional image sequences, the optical flow is formulated as a global energy functional:

E= + +)] dxdy

Where , I and are the derivatives of the image intensity values along the , and time dimensions respectively,, are the components of the optical flow, and is regularization constant. As the solution depends on the neighbouring values, when the neighbour pixels are updated, the solution needs to be iterated. In an iterative scheme, the optical flow can be written as:

D.HOF Descriptor

The feature descriptor is fixed dimensional features derived from optical flow field estimated in a frame. HOF is similar to Histograms of Oriented Gradients (HOGs) [6], but they are computed quite differently. HOF is also different from the descriptor proposed where the differential optical flow is considered. Here, HOF descriptor is computed over dense and overlapping grids of spatial blocks, with optical flow orientation features extracted at fixed resolution and gathered into a high dimensional feature vector.

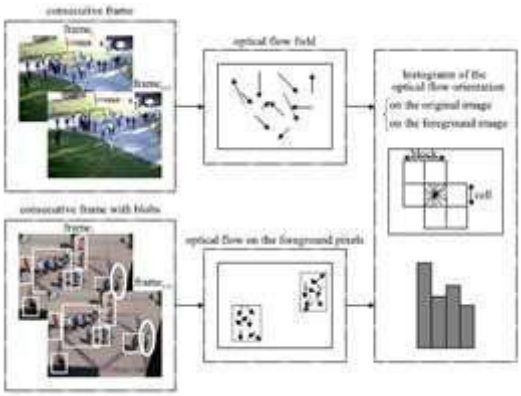


Figure 3 Histogram of optical flow (HOFO) of the original global image and of the foreground image obtained after applying background subtraction.

Fig. 3 illustrates the HOFO feature descriptor of the original image and for eground image. Horizontal and vertical optical flows vote into orientation bins into cells where HOFO is computed. A weighted vote of each pixel is calculated for the edge orientation histogram channel based on the optical flow element orientation cantered on it, and then the votes are gather edinto orientation bins over local spatial regions. The optical flow magnitude of a pixel is considered as a weight in the voting process. The calculation procedures of HOFO in original frame and for eground frame are similar.

The HOF feature is computed at each block and then concatenated into one monolithic vector denoted as for frame . The HOF of each frame is a vector of dimension - × - . The orientation bins are evenly spaced 12 parts over 0°-360°. The HOF is computed with an overlapping proportion of two neighbouring blocks. The overlapping proportion of two adjacent blocks is 50%. A block contains × cells of × pixels, where are the number of cells in and direction respectively. The small size of the cells or the blocks will takes more time to compute the HOF feature.

E.SVM Classifier

In this section, we describe the classification method technique. Support Vector Machine (SVM) is a method based on statistical learning theory and risk minimization for classification and regression. SVM is initially proposed by Vapnik and Lerner. Later, SVM has been extended to nonlinear framework with the introductions of kernel methods.. The one-class SVM framework is well adapted to the event detection Problems, especially abnormal event detection where one can just obtain samples in the normal scenes.In one-class SVM, the objective is to find an appropriate region in the space which contains most of the data drawn from an unknown probability distribution . This can be obtained by searching for a decision hyper plane in the feature space $\mathcal{H}$, which maximizes the distance from the origin, while only a small fraction of data falls between the hyper plane and the origin.

F.*Multiclass SVM*

Originally, SVMs were developed to perform binary classification. However, applications of binary classification are very limited especially in remote sensing land cover classification where most of the classification problems involve more than two classes. A number of methods have been proposed to implement SVMs to produce multiclass classification.

Generally SVM is used to classify the test samples to two different classes (True and False). we use multi class classification, it have both true and false samples in our training set, the accuracy is always above 90%, but if we use one class classification (only true samples in the training set), the accuracy is very low. In one class classification, we use radial basic function only. And alsowe have to reduce the computational cost by using multiclass SVM.

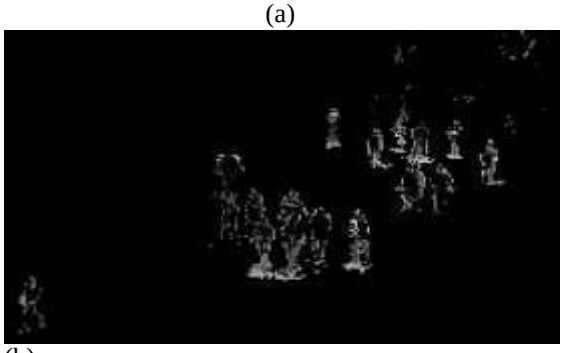
IV. EXPERIMENT AND RESULT

A series of experiments has been conducted to evaluate the proposed approach for event detection. The video datasets which are collected surveillance system have people moments on Public Park, lawn, indoor and plaza et, which are used in experiments to analysis the proposed method of classification of abnormal events. The experimenting datasets have three videos each have 300 frames. The videos containing some frames have different abnormal events caused cycling and moments motor vehicles. The videos containing 50% frames are used for training the SVM classifier and remaining 50% frames used for testing the classifier performance. Model of surveillance system carried out by two steps. The first steps for segmenting object from background and connected component and seconds steps for classification whether the objects are cause of abnormal events. Segmenting the background from the input image by using GMM.

Every pixel on the frame is modeled with Mixture of K (K=3) number of Gaussians function parameters (μi, σi, ωi). μ_i mean and σ_i standard deviation of i_{th} component ω_i weight of i_{th}

component. Each component is update on every pixel which is observed as background pixel. The confidence interval of the pixel value measured against Gaussian distribution using these parameters. If this interval distance > 2.5 σi is set as foreground otherwise background pixel.

(a)



(b)

Figure 4(a) Input image, (b) Foreground of a Frame. Segmenting foreground from input image by using GMM

In order to separate object moving on frame, the connected component labelling algorithm finds all objects in an image and assigns a unique label to all points in the same object.After background subtraction, morphological process holes filling and BW labelling with 4 neighbours carried out on binary image.

The *u* and *v* denote horizontal and vertical vector of moving objects. Initially u and are set to zero and then Horn-Schunck (HS) used to estimate optical flow from gradient changes of 4 neighbouring pixels between current frame with reference to previous frame. The algorithm iterated over and over until there no changes between current and previous iteration.

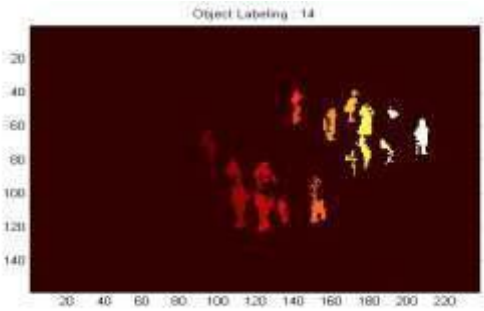


Figure 5 Moving object of the Frame

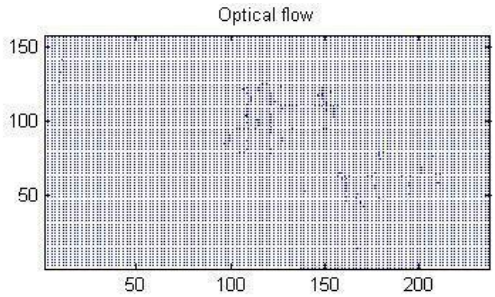


Figure 6 u and v vector of quiver plot

The histogram optical descriptor examined with optical flow fields of orientation. The optical flow fields are divided into overlapping blocks and each block's orientation is discredited as 12 bins of the histogram. The HOFO is computed on the global foreground image, the background area is not considered when the HOFO is being calculated. The time ratio between computing the HOFO of foreground patches and computing the HOFO of the whole *image* is A^{fg}/A^{img}, where A^{fg} is the area of the foreground, A^{img} is the area of the whole image. The accumulated block frequency of orientation histogram had shown on figure for u and v vector field respectively.

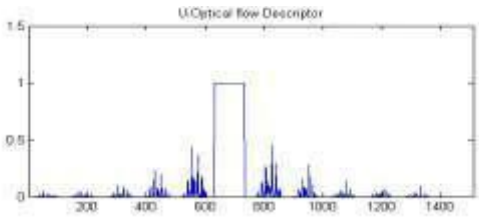


Figure 7 Histogram descriptor of u vector of optical flow

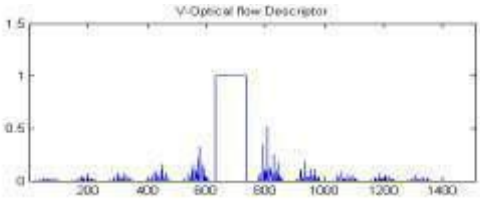


Figure 8 Histogram descriptor of v vector of optical flow.

Input Image

Abnormal Object

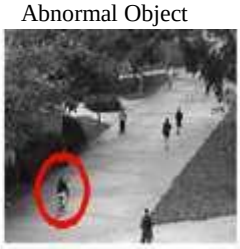


Figure 9 AbnormalObject Identification

On training process, the input frame read from videos is segmented into moving objects using background subtraction model and connected component techniques. The each object's moving velocity vector estimated from optical flow model and then optical flow field (vector) is converted into optical descriptor using histogram bins represented by optical vector orientation. The training samples and the normal testing samples are extracted from the individuals are walking in different directions.

The abnormal testing samples are the frames where the vehicles are moving in same direction. The accuracy of abnormal detection results before state transition post-processing is 90.00%.The figure shown final output of the SVM classifier which was trained with normal objects and abnormal objects optical flow features.

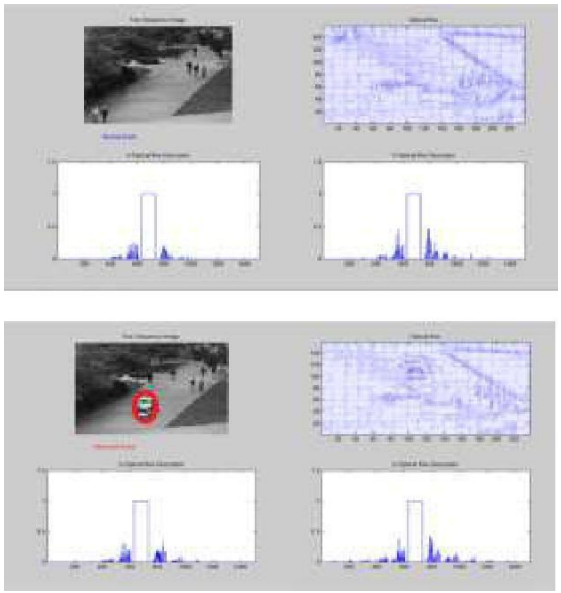


Figure 10 (a) Normal event,(b) Abnormal events

The experimental results show that our proposed method can successfully discriminate normal events and anomalous action and also detecting the object which are creating the anomalous action. Our feature is based on the optical flow can be obtained by HS method, whereas there are other methods that can compute precise optical flow. If a more precise optical flow can be obtained, the more robust abnormal detection results that our HOFO based method can provide tan this paper. Our proposed method can give satisfactory abnormal detection results.

V.CONCLUSION

A method for abnormal event detection is proposed. The model of surveillance system carried out by two steps. The first steps for segmenting object from background and connected component and seconds steps for classification whether the objects are cause of abnormal events. The classifier system, support vector machine (SVM) is trained with features extracted from object's optical flow descriptor to classify abnormal objects from normal one. Here Multiclass SVM used for classification.

The HOFO feature descriptor is computed on the original image, and also on the foreground image, which is obtained after applying background subtraction for fast implementation. The HOF feature is for the monolithic or partial frame. The resulting algorithm has been tested on several sequences and we have shown that the method is able to classify potential events, such as whether the object which moves toward the same direction or merely the velocity is changed. The proposed detection algorithm has been tested on several video datasets yielding successful results in detecting abnormal events

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