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# Abnormal Event Detection in Video using Appearance and Motion Information

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***Abstract*—*This paper presents associate approach for the detection and localization of abnormal events in pedestrian areas. The goal is to style a model to observe abnormal events in video sequences exploitation motion and look info. Motion info is described through the employment of the speed and acceleration of optical flow and also the look info is described by texture and optical flow gradient. Not like literature ways, our planned approach provides a general resolution to observe each international and native abnormal events. What is more, within the detection stage, we have a tendency to propose a classification by native regions.*

***Keywords*—** *Abnormal event detection, video analysis, spatiotemporal feature extraction, video surveillance.*

## I. INTRODUCTION

In recent years, abnormal event detection in video has attracted a lot of attention within the pc vision analysis community thanks to the increased specialize in automatic police work systems to enhance security publicly places, such as: airports, railway stations, looking malls, etc. historically, video police work systems area unit monitored by human operators, World Health Organization alert if there area unit any suspicious events on the scene. However, human eye is liable to distraction or temporary state thanks to long hours of observation. Additionally, the connection between human operators and therefore the sizable amount of cameras is disproportionate, creating it a lot of difficult to find and answer all abnormal events that occur on the scene. This motivates the requirement for an automatic abnormal event detection framework victimization pc vision technologies. associate degree abnormal event has no consistent definition, because it varies per the context. In general, it's defined as a happening that stands out from the conventional behavior inside a specific context. During this work, we have a tendency to take into account the context of pedestrian walkways, wherever the conventional behaviour is performed by individuals walking. Events that involve speed violations and therefore the presence of abnormal objects area unit thought of to be abnormal. We have a tendency to gift associate degree approach for the detection and localization of abnormal events in video victimization motion and look info.
Motion info is painted through the utilization of the speed and acceleration of optical flow and look info is painted by the textures and optical flow gradient. To represent these options we have a tendency to use non-overlapping spatio-temporal patches. Not like literature ways, our model provides a general answer to find each, international and native abnormal events. what is more, the detection stage presents issues of perspective distortion, this occur thanks to the objects close to the camera seem to be massive, whereas objects faraway from the camera seem to be little. To deal with these issues, we have a tendency to propose a classification by native regions.

## II. PROPOSED METHOD

In this section, we present our approach for abnormal event detection. We use different sets of features to model the normal events and to detect different anomalies related to speed violations, access violations to restricted areas and the presence of abnormal objects in the scene.

## III. FEATURE EXTRACTION

In order to limit the analysis to regions of interest and to filter out distractions (eg. waving trees, illumination changes, etc.), we tend to perform foreground extraction on every incoming frame. During this work, we tend to calculate the foreground by the binarization of the subtraction of 2 consecutive frame, generating a foreground mask. Additionally, to estimate the optical flow field of every frame, our approach considers the Lucas-Kanade pyramidic optical flow algorithmic program. It's necessary to notice that solely the optical flow of the foreground pixels is calculated. Our approach divides the video sequence into non-overlapping spatio-temporal native patches of $m \times n \times t$. for every spatio-temporal patch P, we tend to extract options supported motion, like rate and acceleration of optical flow, and options supported look, like textures and gradients of optical flow. The extraction method of every of the options is shown below.
*Velocity:-* The optical flow velocity feature is the summation of optical flow vectors inside a spatio-temporal patch
*Acceleration:-* The optical flow acceleration feature extracts data regarding the temporal variation of optical flow [5]. To model this feature, we tend to calculate the optical flow of every incoming frame and so reckon the optical flow magnitude of every foreground element, the magnitude is normalized between [0,255] to make a magnitude image. Again, we tend to reckon the optical flow of the magnitude image to calculate the acceleration. Finally, for every spatiotemporal patch the acceleration data is calculated by a summation of the acceleration vectors.
*Textures of Optical Flow:-* The textures of optical flow live the uniformity of the motion [6]. This feature is computed from the scalar product of flow vectors at different offsets p

and p0 = p+δ, wherever δ denotes the displacement of the pixel p.

*Histogram of Optical Flow Gradient (HOFG):-* This feature extracts info concerning the abstraction variation of optical flow [5]. To model this feature, we tend to first treat each horizontal and vertical optical flow elements as a separate image so reckon the gradients of every image mistreatment Sobel operators. For every spatio-temporal patch, we tend to generate a four-bins bar graph in every image employing a soft binning-based approach and finally concatenate each histograms into one eight-dimensional feature vector.

## IV. Abnormal Event Detection

In universe, sometimes traditional event samples square measure predominant, and abnormal event samples have very little presence. Due to this, the detection of abnormal events becomes even a lot of difficult. During this paper, to handle this downside, we tend to use the classification methodology planned in [3]. In [3], the classification stage uses the minimum distance. The most plan of this classification methodology is to go looking trained pattern that square measure kind of like the incoming pattern. That is, if the incoming pattern is analogous enough to a number of the noted patterns, then it's thought of as a traditional pattern. Otherwise, it'll be thought of as Associate in Nursing abnormal event. However, the classification supported the minimum distance gifts issues of detection thanks to some videos present the angle distortion within the scene. That is, objects as regards to the camera seem to be giant whereas distant objects seem to be little. This {will|this could|this may} significantly affect the feature extraction strategies because the extracted options will vary in keeping with their depth within the scene. During this paper, to handle the matter of perspective distortion and to get higher results, we tend to propose a classification supported native regions. This classification methodology divides the scene into native spacial regions in keeping with the depth of the scene, wherever traditional patterns square measure sculptured in every native region.

## V. Experimental Setup and Datasets

The final feature vector contains 2 options describing the horizontal and vertical optical flow fields (velocity), 2 optical acceleration options (horizontal and vertical directions), 3 options of optical flow textures and eight-dimensional bar graph of optical flow gradient elements, four elements for every vertical and horizontal directions. Therefore, we've a fifteen-dimensional feature vector for every spatio-temporal patch. Additionally, we tend to by experimentation set a fixed spatio-temporal patch size of twenty × twenty × seven. The criterion wont to value abnormal events detection accuracy was supported frame-level.

UMN dataset consists of 3 different scenes of thronged escape events with a 320 × 240 resolution. The conventional events square measure pedestrians walking haphazardly and therefore the abnormal events square measure human unfold running at an equivalent time. There square measure a complete of eleven video clips within the dataset. Within the coaching section the first three hundred frames of every video were wont to model traditional events and therefore the remaining frames were employed in the check section. UCSD dataset includes 2 sub-datasets, Ped1 and Ped2. The gang density varies from distributed to terribly thronged. The coaching sets square measure all traditional events and therefore the testing set includes abnormal events like cars, bikes, motorcycles and skaters. Ped1 contains thirty four video clips for coaching and thirty six video clips for testing with a 158×238 resolution, and Ped2 contains sixteen video clips for coaching and twelve video clips for testing with a 360×240 resolution.

## VI. Conclusions

In this paper, we have a tendency to propose a replacement approach primarily based within the motion and look info for abnormal event detection in huddled scenes. Motion options are appropriate for police investigation abnormal events with high speed motion. However, some abnormal events have a standard speed, to deal with this kind of events; we have a tendency to introduce the utilization of look options. Moreover, we have a tendency to propose a replacement classification methodology supported native regions to deal with the issues of perspective distortion in videos.

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