

Detecting Events in Crowded Environments using Hybrid Motion Estimation Technique

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Abstract:

The widespread use of surveillance systems in roads, stations, airports or malls has led to a huge amount of data that needs to be analyzed for safety, retrieval or even commercial reasons. The task of automatically detecting frames with anomalous or interesting events from long duration video sequences has concerned the research community in the last decade. Event, and especially anomaly detection in crowded scenes is very important, e.g. for security applications, where it is difficult even for trained personnel to reliably monitor scenes with dense crowds or videos of long duration. This project focuses on detecting and localizing anomalous events in videos of crowded scenes, i.e., divergences from a dominant pattern. Both motion and appearance information are considered, so as to robustly distinguish different kinds of anomalies, for a wide range of scenarios. We propose hybrid full search motion estimation technique to detect the moving vehicle in the road. Then, the background

subtraction algorithm is applied to detect the moving object and also it is used to recognize whether the detected object belongs to vehicle or human using template matching algorithm.

Moving object detection is the basic step for further analysis of video. Every tracking method requires an object detection mechanism either in every frame or when the object first appears in the video. It handles segmentation of moving objects from stationary background objects. We use the temporal information computed from a sequence of frames to reduce the number of false detections. This temporal information is usually in the form of frame differencing, which highlights regions that changes dynamically in consecutive frames.

I.Introduction

Moving object detection is low-level, important task for any visual surveillance system. One of the aims of this project is to, to describe various approaches of moving

object detection such as background subtraction, temporal difference. A statistical mean technique is used to overcome the problem in previous techniques. We propose a modified statistical mean technique with noise removing process that is computationally fast, by allowing the parallel processing. This paper also presents an effective traffic surveillance system for detecting and tracking moving vehicles in nighttime traffic scenes. The proposed method identifies vehicles by detecting and locating vehicle headlights and taillights using image segmentation and pattern analysis techniques. This proposed technique, overcome the drawbacks of traditional approach of moving object detection.

The widespread use of surveillance systems in roads, stations, airports or malls has led to a huge amount of data that needs to be analyzed for safety, retrieval or even commercial reasons. The task of automatically detecting frames with anomalous or interesting events from long duration video sequences has concerned the research community in the last decade. Event, and especially anomaly detection in crowded scenes is very important, e.g. for security applications, where it is difficult even for trained personnel to reliably monitor scenes with dense crowds or videos of long duration. Numerous methods have been proposed to assist in this direction.

The analysis of motions and behaviors in crowded scenes constitutes a challenging task for traditional computer vision methods, as barriers like occlusions, varying crowd densities and the complex stochastic nature of their motions are difficult to overcome. Computational cost is one more complicating factor, as it has to be kept within reasonable limits. In many practical situations, it is crucial to analyze crowded scenes in real time, or at least as fast as possible, considering the fact that security

personnel should act quickly if something seems to be “not as usual.” Furthermore, the ambiguity of the term “anomaly” sets its own limitations in our effort to identify it, as there is no commonly accepted definition, and it varies significantly depending on the given scenario. This means that an “anomaly” pattern in one video sequence may often be part of the “normal” pattern of another. In order to address these issues, we define as “anomalies” the events that display a low probability of occurring based on earlier observations. We deal with the challenging problem of detecting abnormal patterns in videos of crowded scenes that emerge as spatiotemporal changes, both in motion and appearance. An appearance-related anomaly would be, e.g. a bicycle passing through a crowd. Moreover, sudden changes in velocity, like an abrupt increase of its magnitude and the dispersion of individuals in the crowd are detected, indicating that something unusual and potentially dangerous may have occurred.

Tracking is closely related to constructing correspondences between frames. Traditional tracking approaches focus on finding *low-level* correspondences based on image evidence. Online models for low-level correspondences are generally employed to adapt to the changing appearances of the target [1]–[3]. However, one notable shortcoming of these online models is that they are constructed and updated based on the previous appearance of the target without much semantic understanding. Therefore, they are limited in predicting unprecedented states of the target due to significant view changes and occlusion, and easily drift in the case when the appearance of the target changes too fast. Figure 1(a) shows an example where the visual appearance of the target changes dramatically in a very short time period, making low-level image correspondences unstable. Without other information, it is

very likely to cause tracking failure, no matter what online model is used. However, if we can recognize this target as a car at a higher level, the tracking task becomes to find the same *car* in the subsequent images instead of finding the object with the same low-level appearance. Therefore, the discriminative information provided by the car category, i.e., the *high-level* correspondences, can be utilized to help successfully track the target. In other words, to make tracking consistently effective in various challenging scenarios, it is necessary to combine both low-level and high-level correspondences. Some offline-trained high-level detectors with semantic meanings have already been introduced into the tracking-by-detection scheme for some specific tracking tasks, especially for human tracking [4]–[6] and vehicle tracking [7], which largely improves the tracking performance. However, these models assume the semantic meanings of targets are already known before tracking, and accordingly cannot be applied to many general applications. Consider a video surveillance scenario with a complex scene, the categories of the moving objects cannot be predicted. Nevertheless, every moving object should be correctly tracked for subsequent analysis, no matter whether it is a human, a car or even an animal. In other cases, the category of the target might change because of object morphing and camouflage (e.g., in Fig. 1(b) the states of the hand are switching between “rock”, “paper”, “scissor”), in which those pre-determined detectors are likely to fail. After all, tracking is not the final goal of video analysis but an intermediate task for some succeeding high-level processing like event detection and scene understanding. Essentially, an ideal tracking system should *actively understand* the target, and adaptively incorporate high-level semantic correspondences and low-level image correspondences. Towards this end, this

paper proposes a unified approach for object tracking and recognition. In our approach, once an object is discovered and tracked, the tracking results are continuously fed forward to the upper-level video-based recognition scheme, in which dynamic programming is adopted to recognize the category of the object in the current frame. Based on the feedback from the recognition results, different off-line models dedicated to specific categories are adaptively selected, and the location of the tracked object in the next frame is determined by integrated optimization of these selected detectors and the tracking evidence.

II. RELATED WORKS

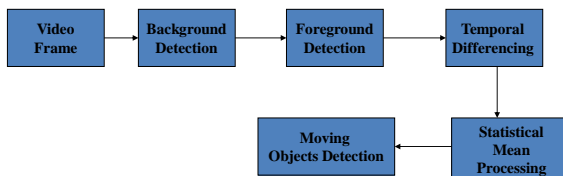
The surveillance system typically uses stationary sensors to monitor an environment of interest. The stationary sensor allows the use of the frame difference (FD) technique and the background modeling technique for detection of moving object, since interesting objects in a fixed scene are usually defined to be moving ones [1]–[10]. The FD is based on simply observing difference between two adjacent frames. By setting a threshold value, a pixel is identified as foreground if the statistic associated with the observation is higher than the threshold value. Otherwise the pixel is identified as background [1]–[14]. To achieve real-time detection with specified video format, several hardware-oriented foreground detection algorithms are presented. Morimoto *et al.* proposed boundary-scan-only foreground detection architecture and its FPGA-based prototype system for 80×60 sized video sequences [15]. Since a huge amount of frames is available and no scene change is occurred between frames, the detection of foreground cannot be restricted to observe difference between two adjacent frames. Instead, the large amount of frames is used as the observation period for making

foreground/background decision. Such approach is called background modeling approach [16]-[18]. The mixture of Gaussian (MoG) [19]-[20] and the non-parametric model [16]-[18] are two typically used models. To achieve real-time processing, some simplifications are presented for the most computationally intensive part, the background model constructing. Tsai *et al.* presented a VLSI architecture using multiple background maintenance technique. The constructing background model in the architecture is based on look-up-table manner. Jiang presented a simplified mixture of Gaussian (SMoG) algorithm and its architecture design. To overcome such dynamic background problem, the issue of tolerating background motions while detecting foreground motions is explored, and various sophisticated background modeling approaches are presented. However, such approaches substantially increase the hardware cost and are not easily realized for real-time application.

the object first appears in the video. It handles segmentation of moving objects from stationary background objects. We use the temporal information computed from a sequence of frames to reduce the number of false detections. This temporal information is usually in the form of frame differencing, which highlights regions that changes dynamically in consecutive frames. Object detection can be achieved by building a representation of the scene called the background model and then finding deviations from the model for each incoming frame. Any significant change in an image region from the background model signifies a moving object. The pixels constituting the regions undergoing change are marked for further processing. Temporal differencing method uses the pixel-wise difference between two or three consecutive frames in video imagery to extract moving regions. It is a highly adaptive approach to dynamic scene changes. Let $I_n(x)$ represent the gray-level intensity value at pixel position x and at time instance n of video image sequence I , which is in the range $[0, 255]$. T is the threshold initially set to a pre-determined value. Two-frame temporal differencing scheme suggests that a pixel is moving if it satisfies the following:

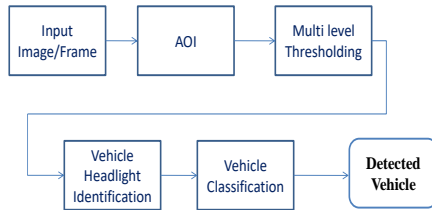
III. PROPOSED SYSTEM

Proposed Object Detection Model:



Moving object detection is the basic step for further analysis of video. Every tracking method requires an object detection mechanism either in every frame or when

Proposed system model for vehicle detection and Classification:



Fast bright-object segmentation process based on automatic multilevel histogram thresholding. Locating headlights and tail lights using the connected components analysis. Spatial clustering process for grouping these bright components to obtain groups of vehicle lights. Feature based vehicle tracking. Feature based vehicle identification and Classification. Lines of roads and divider are detected using Hough transform. Draw the line which passes through the middle of the image in horizontal direction. AOI is the region between the middle line and detected road boundaries.

PROCEDURE FOR DETECTION OF ROAD LINE SEGMENTS:

➤ **STEP1:**

- Convert the Road Image in to two binary Images using Threshold method.
- By doing repeated experiments, we set threshold as 50.
- At this stage ,the road region is not exactly separated.
- To exactly separate or locate the boundary of the Road region, we use Edge detection followed by Hough Transform.

STEP2:

- Find the Edge Image from the foreground Image(Road Image) using ‘canny’ Edge Detection method.

STEP3:

- Apply Hough Transform.
- It detects the line in the binary Image for the particular Orientation Image.
- The hough function implements the Standard Hough Transform (SHT). The SHT uses the parametric representation of a line:
- $\rho = x*\cos(\theta) + y*\sin(\theta)$
- Where θ =particular Orientation(1,2,3,.....180).
- At this stage, we get 180 Hough Transformed Images.
- From these 180 Images, find the image which have most possible line segments.
- To find the maximum length line segment, apply morphological operation.
- Morphologically open binary image(bwareaopen) is used to remove small objects.
- It removes the smallest line segments by keeping the boundry lines of the Road Image.
- Choose each pixel in the morphological opened Road Image.
- If the pixel(I)==0,no change will be made in the Original Color Road Image.
- If the pixel(I)==1,Change the Corresponding ‘R’ Component pixel value to 255 and G=0 and B=0 of that Particular Pixel.
- To preliminarily screen out non vehicle illuminating objects, such as street lamps and traffic lights located at the top side of traffic scenes, and to effectively and rapidly locate the sufficiently reliable and clear features of moving vehicles, and

efficiently save the redundant computational costs for the embedded system implementation, we apply a detection area for each traffic scene.

- This detection area is the midline of the traffic-scene image and bounded by the most left and right lanes.

IV. Simulation Results

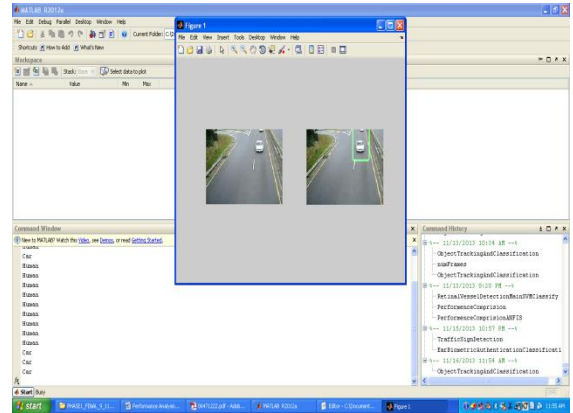
Illustration of detection area of traffic scenes



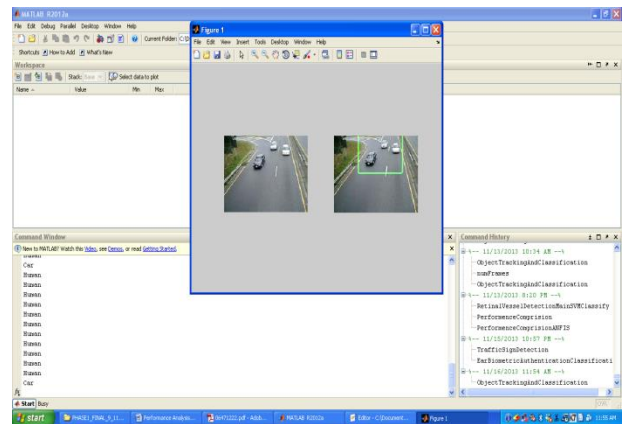
Extracted bright components in the detection area

The RGB Image is converted in to Ycb Cr image. Y is the luminance or gray scale image. The thresholding is applied on the Y components only to extract the bright objects. In our proposed work, multilevel thresholding is used to separate the light source of the vehicles from other bright objects.

Simulation Screenshot for traffic.avi video:



Simulation Screenshot for trafficinput2.avi video:



Performance Analysis:

Video Type	Existing	Proposed
Number of frames	120	120
Video width	160	160

Video Height	120	120
Processing Time in Sec per frame	0.3519	0.2519
False Negative Rate	0.3761	0.2083
Accuracy	62.39	79.17

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