Computationally Efficient Algorithm for Tracking of Vehicles in Tunnels

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***Abstract*—We propose a computationally efficient algorithm for detection and tracking of moving vehicles in tunnels. The approach uses a thresholded single frame difference (TSFD) image and an efficient projection scheme through so-called scan lines. A rigid nature of vehicles (especially their consistent size) is used to deal with the problem of threshold sensitivity which occurs in frame difference images. Experiments show that the proposed approach is efficient even when color of moving vehicles is similar to the background color and that it is not sensitive to the illumination change which appears when big vehicles (e.g. buses or trucks) enter the scene.**

***Index Terms*—moving object detection, single-camera tracking.**

I. Introduction

Intelligent computer vision systems can improve safety in tunnels, which are especially dangerous environments prone to horrible traffic accidents. There is a strong trend towards automatic tunnel management by exploitation of video material from security cameras. The problems that need to be solved are automatic detection and tracking of vehicles in acquired video sequences. Since it is very important for traffic control operators to notice the potentially incidental situations as quickly as possible and regarding the fact that tunnel surveillance systems nowadays have dozens of cameras, algorithms created for this application have to be computationally very efficient and robust.

So far, numerous techniques for the detection of moving objects have been proposed. The most common approaches, for videos acquired by a stationary camera, use background modeling with a goal of background suppression and foreground segmentation. These approaches are often based on inter-frame difference if the frame rate is high enough and if objects are rigid. There are several ways of calculating inter-frame difference and according to that their names are given: single difference (difference between two consecutive frames), double difference (calculated using three consecutive frames) and accumulative difference (calculated using more than three consecutive frames). For computational simplicity, we apply single frame difference as an initial step of our algorithm. The main novelty is moving object detection based on a simple combination of vertical and horizontal scan lines. We introduce an occupancy scheme made by vertical and horizontal scanning of the TSFD images and in combination with higher level information (a priori known minimal possible moving objects dimensions) we use it for the detection of moving vehicles.

We evaluate our algorithm on real life tunnel sequences and compare the results with a well-known Li et al. algorithm [15] which uses Bayesian framework for Gaussian mixture background modeling. Our algorithm is less sensitive to the color of moving vehicles and lighting. This is very important in tunnel environment because of tunnel artificial light under which colors look usually washed out and similar to the environment color. Our algorithm is also less sensitive to the illumination changes which appear when big vehicle enters the scene.

The remaining of the paper is organized as follows. In Section II we first describe the specific problems of the background modeling and the background changes in tunnel surveillance videos. Then we give specification of the foreground detection problem and present the computationally efficient algorithm for the detection and tracking of vehicles in tunnels. The experimental results on two real life tunnel sequences are presented in Section III. The paper is concluded in Section IV.

II. Detection of moving vehicles

A. Problem Specification

In video processing, the background is considered as the scene without the presence of objects of interest (which are considered as foreground).

In tunnels, which are a specific combination of indoor and outdoor environment, sets of possible background and foreground objects are different from other environments. The stationary background objects can be walls and ceiling from a tunnel pipe, road and stationary signalization signs. The moving background objects can be non-stationary signalization signs (all kind of signs and displays the content of which changes automatically). Background can also change over time due to light reflection from background and foreground objects. This reflection can be very intensive if the big objects (e.g. buses or trucks) enter the scene, or if the road is wet. The foreground objects are moving vehicles. A foreground object might also become a background object, e.g. if vehicle stops. Because of the artificial light in tunnels, colors of vehicles look usually washed out and similar to the environment color. The methods which employ one type of features or integrate multiple features to model the background on pixel level have adaptation problem to the fast and intensive illumination change.

Therefore, we use a rigid characteristic of vehicles (a priori known minimal possible dimensions of the vehicle) as a higher level information, to differentiate moving vehicles from other moving objects and to decrease sensitivity to the illumination change.

B. Algorithm description

Our algorithm detects moving objects in Thresholded Single Frame Difference (TSFD) images. These images are obtained by subtraction of two consecutive frames and thresholding (see Fig. 1(b)). In typical TSFD images "gaps" appear within the moving objects. For this reason, single frame difference images are mostly used only for the detection of motion presence and not for the detection of moving objects. The main idea of our approach is to detect the moving objects using projections of the TSFD images through scan-lines.

The scan-line technique is illustrated in Figure 1(c). If one pixel value along the line in the scanning direction is white, so is the corresponding value in the scan line. In this way we create motion occupancy scheme and locate moving objects within the image.

We are first scanning the TSFD image vertically (in the direction of the traffic flow) to locate potential moving objects. In order to reduce false detections, we define a priori known minimal possible dimensions of objects of interest (vehicles) and discard the areas in the scan line that are too narrow (and usually result from shadow, light reflection or noise). In the detected areas, we additionally scan horizontally to estimate the moving object boundaries. There we employ two additional thresholds: for a minimal object height and for a tolerance to missing object parts in the TSFD image (Figure 2). We use a threshold for the minimal object height to avoid detection of moving "objects" which are not vehicles (e.g. shadow, light reflection or noise).

Figure 1. (a) Top: An input image from a tunnel. There is a static vehicle in the most right lane. (b) Middle: The corresponding thresholded single frame difference (TSFD) image. (c) Bottom: The resulting scan line. The areas designated by the arrow are discarded due to the minimum width constraint.

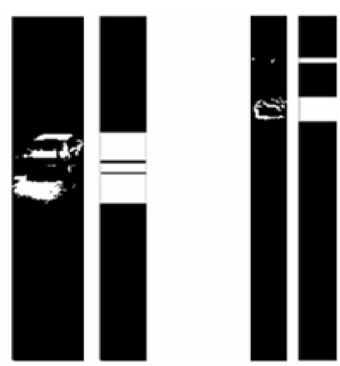

Figure 2. Two parts of the TSFD image according to the Fig. 1. and their corresponding horizontal scan lines used for the estimation of object boundaries.

For tracking of the detected vehicles we make use of overlapping between the same vehicles in two consecutive frames. The whole algorithm is presented in Figure 3. The result of the algorithm on the frame from Figure 1 is presented in Figure 4.

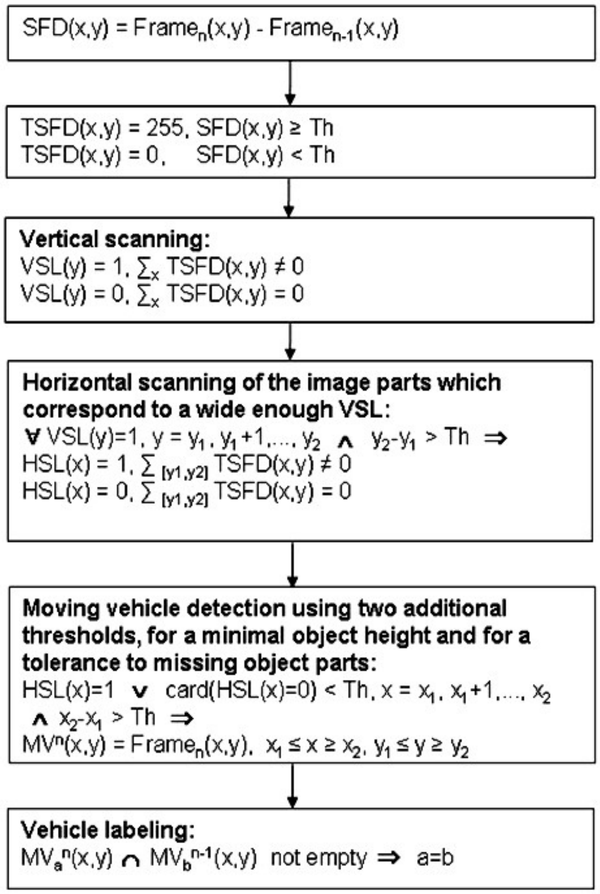

Figure 3. The algorithm diagram. $\mathrm{VSL}(y)$ = vertical scan line; HSL(x) = horizontal scan line; $\mathrm{MV}_a^n(x, y)$ = detected moving vehicle labeled a in frame n.

Figure 4. The result of our object detection algorithm on the frame from Figure 1. The moving vehicles are detected and the static vehicle is not detected.

III. Experimental results

We evaluated our algorithm on real life sequences from several European tunnels and compared the results with an algorithm presented by Li et al. [15] which uses Bayesian framework for Gaussian mixture background modeling on a pixel level. Figures 5 and 6 show the results on two different tunnel videos. One is in color (Figure 5) and the other one is a grayscale video (Figure 6). Our algorithm is less sensitive to the color of moving vehicles and lighting (see Figure 5(a) and Figure 6). Our algorithm is also less sensitive to the illumination change which appears when big vehicle (e.g. bus or truck) enters the scene (Figure 5(b)). Nevertheless, our algorithm performs the same in situations when vehicles are in distance or partially occluded. Our algorithm is less precise in the detection of moving vehicle boundaries (it detects part of the background as part of the moving vehicle, because of presence of ghosts and shadows of moving vehicle in TSFD images).

IV. Conclussion

Using occupancy scheme made by vertical and horizontal scanning of the TSFD images, in combination with higher level information (a priori known minimal possible moving objects dimensions) performs well for detection of moving vehicles in tunnels. On the other hand, algorithms which use background modeling on a pixel level have problems with adapting to the fast and intensive change of the background. Tracking of detected moving vehicles using overlapping between the same vehicles in two consecutive frames performs well if the frame rate is high enough. The proposed algorithm is robust, easy to compute and to integrate in embedded systems solutions.

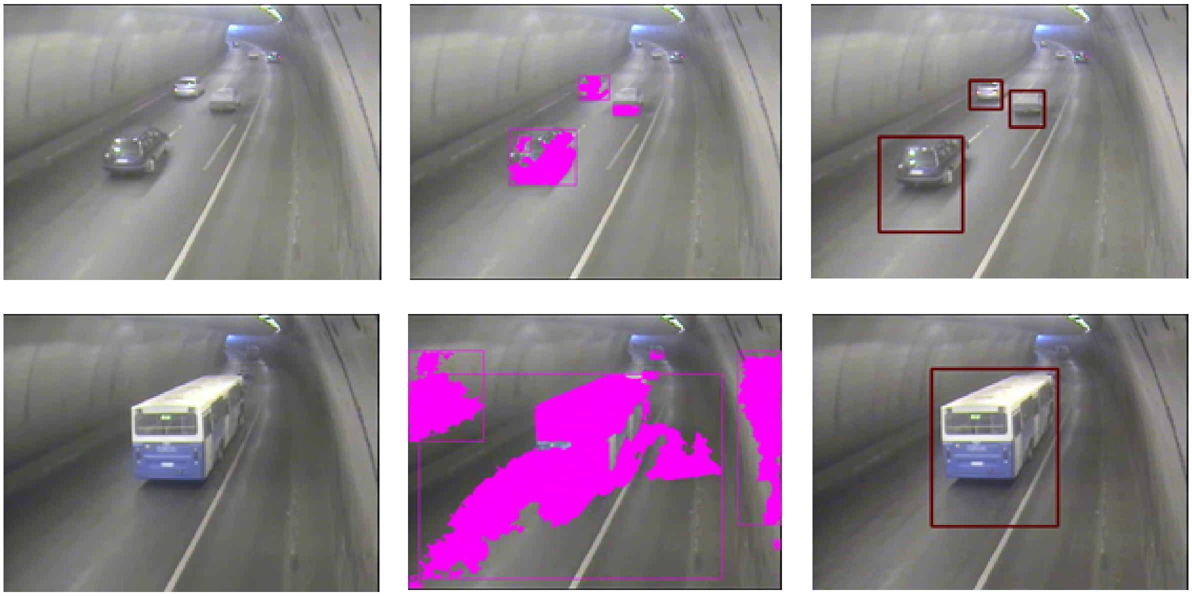

Figure 5. The results on a color sequence. (a) Top row. Left: An input image from a tunnel; Middle: The algorithm from [15]; Right: The proposed method. (b) Bottom row. Left: An input image from a tunnel; Middle: The algorithm from [15]; Right: The proposed method.

Figure 6. The results on a grayscale sequence. (a) Left: An input image from a tunnel. (b) Middle: The algorithm from [15]. (c) Right: The proposed method.

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