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Reliable moving vehicle detection based on the filtering of swinging tree leaves and raindrops

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ABSTRACT

An efficient method for detecting moving vehicles based on the filtering of swinging trees and raindrops is proposed. To extract moving objects from the background, *an adaptive background subtraction scheme with a shadow elimination model is used*. Swinging trees are removed from foreground objects to reduce the computational complexity of subsequent tracking. Raindrops are removed from foreground objects when necessary. Performance evaluations are carried out using seven real-world traffic image sequences. Experimental results show average recognition rates of 96.83% and 97.20% for swinging trees and raindrops, respectively, indicating the feasibility of the proposed method.

1. Introduction

The detection of moving vehicles in a video sequence is an important research field due to its applicability to automated visual surveillance systems, traffic monitoring systems, and crime prevention systems. However, existing approaches are affected by luminance variation, weather change, camera jitter, and image noise. For example, some environmental factors, such as swinging trees and raindrops, in traffic monitoring systems greatly impact the tracking performance of vehicles. A robust tracking system is thus desirable.

For a traffic monitoring system, the removal of swinging trees and raindrops is of great importance because they are often erroneously detected as moving vehicles or pedestrians based on background subtraction schemes. Detected objects that are the parts of backgrounds increase the computational burden of the subsequent tracking of real moving objects, such as vehicles and pedestrians, if they are not removed. For most traffic surveillance systems [1,2], the effects of such environmental factors on tracking performance are rarely considered, which limits the systems in some practical applications. The present study thus considers the effects of swinging trees and raindrops on vehicle detection in the proposed system.

For most computer vision-based applications, motion detection that aims to segment regions corresponding to moving objects is of great importance for the subsequent processes of analysis, recognition, and tracking of those objects. Motion detection can be achieved using techniques which can be roughly classified as background subtraction [3,4], temporal differencing [5,6], optical flow [7,8] methods, and block motion estimation [9,10]. Background subtraction can extract the pixels in image sequences with the most discriminative power but it is extremely sensitive to illumination variation. Temporal differencing adapts to dynamic environments but its performance in extracting relevant features is poor. Optical flow can detect moving objects in the presence of camera motion but it is computationally expensive. Block motion estimation can reduce the intensively computational complexity required by the optical-flow method but the accuracy may be also reduced.

Background modeling is of great importance for the detection of moving objects in a video sequence. During the last decade, many different methods for detecting moving objects have been proposed [11,12] and several features are used for modeling the background [13]. Stauffer and Grimson [11] modeled each pixel with a mixture of adaptive Gaussians for background estimation to deal with variations in lighting, moving scene clutter, and repetitive motion. In their methods, k-means clustering was used to initially find the center of a mixture of Gaussian distributions through an iterative refinement approach. However, k-means may be very slow to converge because it highly depends on the guess of initial center of each cluster. In contrast to a Gaussian mixture model, Elgammal et al. [12] proposed a non-parametric kernel density

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method for background modeling to alleviate the limitations of parametric methods because the assumption of Gaussian distribution for pixel intensities is not always true. In their method, the probability of pixel intensity distribution is calculated directly from the observations without any assumption of the underlying distributions.

Recently, Heikkilä and Pietikäinen [13] have modeled the background using texture features. The features of local binary pattern (LBP) were used in their method due to its tolerance against lighting changes and its computational efficiency. However, the LBP feature cannot work well if the gray scales of the neighboring pixels are close to the value of the center point. Additionally, many parameters needed to be tuned make this method difficult to be applied to a wide variety of scenarios.

Shadows that can distort the shape of moving objects and thus affect the subsequent task of moving object tracking are a common problem when applying the scheme of background subtraction. To deal with these difficulties, Cucchiara et al. [14] proposed a method that uses the features of statistics, adaptivity, and selectivity to detect moving objects, ghosts, and shadows. In their method, they adopted color information for both background subtraction and shadow detection to improve the performance of object segmentation and background update. In addition, weather effect of raining is also an important factor on the performance of moving object detection. Garg and Nayar [15] developed a correlation model to analyze the visual effects of rains on imaging system. Based on the model, they presented an efficient algorithm for detecting and removing rain from video sequences. Moreover, in their experiments higher brightness of the raindrops than the corresponding background intensities was also observed.

To consider the color information in background modeling, McKenna et al. [16] used an adaptive background subtraction technique for detecting groups of people by estimating three variance parameters of the R, G, and B channels for each pixel in image sequences. In their background model, recursive updates are used to adaptively cope with changes in illumination. Background modeling has also been employed to track moving objects. For example, multivariate Gaussian mixtures have been utilized to model pixel color variations for people tracking [17]. Koller et al. [18] used an adaptive background model based on monochromatic images filtered with Gaussian and Gaussian derivative kernels for car tracking.

Liption et al. [5] segmented moving targets from a real-time video stream using the pixel-wise difference between consecutive frames. Their method can classify humans, vehicles, and background clusters. After classification, targets can be tracked by a combination of temporal differencing and template matching. Zhang and Siyal [6] proposed an improved scheme for segmenting moving objects by using two difference images obtained from three consecutive frames in an image sequence, where the two difference images are pre-processed using a logical AND operation.

Garlic and Loncaric [7] adopted optical flow to extract the feature vectors in a video sequence. The extracted feature vectors are further clustered using a *k*-means clustering algorithm to determine the characteristic image regions, which allows the detection of moving targets. Gutchess et al. [8] incorporated the concept of optical flow into a background initialization problem, where multiple hypotheses of the background value for each pixel are generated by locating periods of stable intensity in image sequences. The likelihood of each hypothesis is then evaluated using optical flow information from the neighborhood around a pixel, and the most likely hypothesis is chosen to represent the background.

Background initialization, foreground detection, and background updating are the three important steps for tracking moving objects in an outdoor space. Object tracking methods [19,20] can be classified as model-based tracking, region-based tracking, active contour-based tracking, and feature-based tracking. In model-based tracking [21], object tracking is carried out by matching a projected object model to image data, where the object model is produced with prior knowledge. In region-based tracking [16], the variations of image blobs corresponding to moving objects in a video frame are detected to achieve object tracking. Active contour-based tracking [22] uses object silhouettes as a bounding contour and updates the contour dynamically in consecutive frames. Feature-based tracking [23–25] matches the features of objects, such as color, area, texture, and shape, between successive frames to achieve object tracking.

Schiele [23] used the color of objects with *k*-means clustering for the extraction and detection of cars as well as people in surveillance scenarios using wearable cameras. Their scheme uses neither *a priori* model of the objects nor a stationary camera; therefore, the results are quite promising. To deal with vehicle tracking in heavy traffic, which may cause parts of vehicles to be occluded, Huang [26] used features instead of whole contours to track multiple vehicles on freeways. In their scheme, the corner features of a vehicle were first detected and then tracked by a Kalman filter. Furthermore, to provide an accurate estimate of the vehicle position in each lane, the detection of lane markers is also performed.

In general, most traffic surveillance systems can work well with good weather conditions like sunny day, or with stationary backgrounds that have no repetitive motions such as swinging trees and fluttering flags. It turns out that most existing algorithms fail to detect moving vehicles in scenes containing swinging trees and/or raindrops since these algorithms often erroneously detect swinging trees and/or raindrops as parts of moving objects. The main contribution of this paper is to integrate the modules of filtering swinging trees and raindrops into the background modeling to further improve the performance of vehicle detection. The major difference of the proposed method with the existing algorithms [15,27–29] for removing swinging trees and/or raindrops is the computational efficiency of the proposed method because our system is operated in a real-time outdoor environment.

The rest of this paper is organized as follows. The proposed method of detecting moving vehicles based on the filtering of swinging trees and raindrops is introduced in Section 2. Experimental results are provided to demonstrate the performance of the proposed algorithm in Section 3. Finally, concluding remarks are given in Section 4.

2. Proposed method

Fig. 1 shows a flowchart of the proposed method based on the filtering of swinging trees and raindrops for moving object tracking. Moving objects are first extracted from image sequences using the schemes of motion detection and background updating. Motion detection is used to analyze the temporal correlation of moving objects in successive frames. A frame difference mask and a background subtraction mask are used to acquire the initial object mask using which the problem of stationary objects in backgrounds can be solved. Moreover, boundary refinement is introduced to reduce the influence of shadows and the problem of residual backgrounds. The segmented objects are further processed by the proposed modules that remove swinging trees and raindrops. By removing these undesired moving objects that belong to the background, the performance of moving vehicle detection is significantly improved.

In Section 2.1, the method of motion detection for moving objects is described. Background updating is introduced in Section 2.2. Then, the method of shadow removal is explained in Section 2.3. Finally, the methods of removing swinging trees and raindrops are given in Sections 2.4 and 2.5, respectively.