VISION-BASED DETECTION OF ACTIVITY FOR TRAFFIC CONTROL

Y. Liu, P. Payeur
Vision, Imaging, Video and Audio Research Laboratory
School of Information Technology and Engineering
University of Ottawa
Ottawa, Ontario, Canada
[yliu055, ppayeur]@site.uottawa.ca

Abstract

One important application of image processing and computer vision is traffic monitoring and control. This paper presents a system for detection of moving vehicles approaching an intersection from color images acquired by a stationary camera in the context of traffic light control systems. As the system is dedicated to outdoor applications, efficient and robust vehicle detection under various weather and illumination conditions is examined. To deal with these ever changing conditions, vehicle detection relies on motion segmentation and color mapping to achieve feature space segmentation. Experimental results using real outdoor sequences of images demonstrate the system's robustness under various environmental conditions.

Keywords: *Motion detection, adaptive background, traffic monitoring, outdoor image processing.*

1. INTRODUCTION

Applications of computer vision in traffic monitoring and control usually rely on motion detection, tracking and feature matching. However, achieving reliable detection of moving objects in natural outdoor environments remains a critical issue as the world under observation continuously changes. Among other things, lighting conditions, time of the day, shadows and weather conditions all influence the content of images. Most existing vision based vehicle detection systems suffer from a lack of robustness in dealing with various natural conditions. In this paper, this aspect is addressed in the context of moving vehicles detection under changing environmental conditions.

In the literature, a large body of vision research has been targeted at motion detection in outdoor scenes based on gray images. Some prototypes work under fair weather situations and clear lighting [1, 2], while others have been developed to operate under specific weather conditions such as snowfall [3] or heavy rain [4], or under low lighting [5].

Cucchiara *et al.* [6] proposed to extract moving vehicles by motion detection and sharp edge closure at daytime while vehicles are identified by their headlights shapes following image thresholding at nighttime. A luminance histogram is used to switch between daytime and nighttime modes. This system succeeds to detect vehicles during the day, whereas it does not consider shadow removal under bright sunny conditions. The approach also tends to classify a significant number of static surface points as moving points when operating in nighttime mode. Detection of actual vehicles also reveals to be less efficient in snowfall conditions during the night. Moreover, as the switching between day and night modes only relies on the luminance parameter, the system has difficulties to cope with wet surfaces that create important reflections.

The most conventional scheme used for extraction of moving-object regions from images is the method of background substraction. Recent improvements introduced in this area consist in implementing a dynamic background updating procedure using a combination of the last few frames [7, 8]. Gupte *et al.* [9] presented such a moving object recognition method by adaptive background substraction to extract vehicles from images. This technique does not require an initial vehicle-free background image and the background representation is adaptive over the time. However, this approach generates erroneous ghosts during the background evolution period, which affect segmentation results.

On the other hand, techniques based on motion and color segmentation have been introduced to detect moving objects by taking advantage of color images [10]. Motion segmentation is obtained by frame differentiation while color segmentation consists of a split-and-merge algorithm that results in an over segmentation of the image to make objects stand out.

In this paper, an approach is introduced to detect moving objects in outdoor scenes with high robustness to weather and lighting variations. The proposed algorithm combines adaptive background representation with hue-saturation-value (HSV) color space mapping to automatically adapt the feature segmentation algorithm. Experimental results using real traffic sequences demonstrate the robustness of the proposed scheme under various weather and lighting conditions.

CCECE 2003 - CCGEI 2003, Montréal, May/mai 2003
0-7803-7781-8/03/$17.00 © 2003 IEEE

2. MOTION DETECTION AND SEGMENTATION

When comparing images collected under various environmental conditions, the perceptual contrast appears to be a critical factor that directly influences the detection of moving objects. Depending on the conditions, the relevant features are so different that designing a single algorithm to cover all cases does not seem suitable. On the other hand, two categories can be clearly defined under a proper mapping of color information. The proposed approach is then based on two detection modes that work in a complementary manner to extract different features from moving regions depending on the current environmental conditions.

The first stage of the system applies motion detection and segmentation on the sequence of images to detect moving regions inside a limited window delimiting the area of interest in the images. Motion detection steps consist of background differentiation, ghost removal, segment filtering and an adaptive background update. The second stage consists of a dual processing scheme that refines the detected motion parameters following two different strategies that depend on the perceptual contrast available in the current set of images.

A selection algorithm is implemented to automatically determine the best mode of operation. The analysis of color image sequences revealed that the HSV color encoding scheme can advantageously be used to distinguish between different weather and illumination conditions. Moreover, under highly contrasting conditions, shadows associated with moving objects need to be detected separately to avoid them being merged with foreground objects. Under nighttime conditions and low perceptual contrast, moving vehicles can only be detected by their headlights as illumination is insufficient. Different templates are then used to detect and locate the relevant features.

2.1 Binary Mask

Starting fromt the RGB color images that are provided by the camera, a pixel-wise difference image is computed between a background representation and the current frame to isolate pixels that are changing with respect to time. The background image contains a representation of all static objects seen by the camera in the area covered by the window of interest. The foreground image to be estimated contains only the detected moving vehicles. The principle of image binarization using a brightness criterion is extended to color images segmentation as color differences appear to be less sensitive to illumination variations and inter-reflections than gray differences. The three color components of the current image, [I_R, I_G, I_B], are compared with the previous background image components [B_R, B_G, B_B] to compute a temporal difference image, $D(x, y, t)$, as follows:

$$D(x, y, t) = \begin{array}{l} |I_R(x, y, t) - B_R(x, y, t-1)| + \\ |I_G(x, y, t) - B_G(x, y, t-1)| + \\ |I_B(x, y, t) - B_B(x, y, t-1)| \end{array} \qquad (1)$$

This difference image is thresholded at a given level, t_D, in order to extract only the pixels where a significant change in all color components has occurred. This results in a binary mask image, M, where pixels that correspond to moving objects have a value equal to one, while all other pixels are set to zero:

$$\begin{array}{ll} M(x, y, t) = 1 & if\ D(x, y, t) > t_D \\ M(x, y, t) = 0 & otherwise \end{array} \qquad (2)$$

The threshold value, t_D, is dynamically estimated from the histogram of $D(x, y, t)$ following an adaptation of the approach proposed in [9]. Depending on environmental conditions, the histogram of $D(x, y, t)$ is more or less spread over the range of difference values. Setting the threshold, t_D, then consists in finding a dip point on the right of the peak of the histogram that has a value significantly lower than the peak value itself. The threshold estimation algorithm is defined as follows:

$$\begin{array}{ll} t_D = d \cdot s & if\ \dfrac{max(D(x, y, t))}{d} > 10 \\ t_D = (d-1) \cdot \dfrac{max(D(x, y, t))}{d} & if\ 0 < \dfrac{max(D(x, y, t))}{d} < 10 \end{array} \qquad (3)$$

where $max(D(x, y, t))$ is the maximum difference value computed between the current frame and the background image, and d is the distance between the peak and the origin of the graph. The parameter s has been experimentally set to 7 in order to achieve good results under all weather and lighting conditions.

2.2 Ghost Removal

As the background image is progressively updated, a vehicle that shows up in the previous background representation influences the detection for a short period of time. While the vehicle evolves inside the search window, its representation in the region that it initially visited progressively fades out but the vehicle may still partially appear even though it is no longer occupying these positions. These regions of the mask image that result from the temporary memory of the background image are called “ghosts” as they do not result from real moving objects. These ghosts affect the validity of the binary mask image, as shown in figure 1b, and must be eliminated.

To do so, the difference between the current and the previous frames is computed over all moving pixels. As ghosts pixels have a small difference between two successive frames since their motion is only apparent, a proper correction can be applied to the binary mask as shown in figure 1c.

Fig. 1. Effect of ghost pixels on binary mask: a) original image, b) mask with ghost pixels, c) mask after ghost removal.

2.3 Adaptive Background

In general, motion tends to generate faster changes in images than illumination and weather conditions. However, keeping the track of environmental factors over the time to allow reliable segmentation between fixed and moving components requires a frequent update of the background image.

To achieve this goal, a temporary background image, $TB(x, y, t)$, is computed. $TB(x, y, t)$ combines the previous background, $B(x, y, t-1)$, for areas corresponding to moving objects with the current image, $I(x, y, t)$, for static areas as follows:

$$TB(x, y, t) = \begin{array}{l} \overline{M(x, y, t)} \wedge I(x, y, t) + \\ M(x, y, t) \wedge B(x, y, t-1) \end{array} \quad (4)$$

where $\wedge$ represents the logical AND operator.

Next, the updated background image, $B(x, y, t)$, associated with the current frame is computed as a weighted average of the temporary background, $TB(x, y, t)$, and the previous background, $B(x, y, t-1)$, as follows:

$$B(x, y, t) = (1-\alpha) \cdot B(x, y, t-1) + \alpha \cdot TB(x, y, t) \quad (5)$$

where α allows to control the background transition rate and is proportional to the ratio of the peak distance from the origin of the histogram of $D(x, y, t)$ and the maximum difference value computed between the current frame and the previous background image, without exceeding 0.5. In practice, this means that when illumination changes are important, the background transition rate is increased as it must map faster variations in the content of the scene. Figure 2 shows an example of a background image updated with the proposed approach.

Fig. 2. Evolution of adaptive background image: a) initial background, b) updated background image after 6s.

2.4 Shadows Detection

Shadows in images generate changes in the adaptive background and tend to be detected as moving components after color segmentation from the difference image. In the proposed approach, this effect is eliminated by discriminating shadows from moving objects taking advantage of the HSV color space mapping [11]. Given the fact that the luminance of the cast shadow is lower than that of the background while the chrominance of the shadow remains similar to that of the background, a shadow mask, $SM(x, y, t)$, is computed to extract pixels corresponding to shadow areas from the set of pixels initially tagged as moving ones in the binary mask, $M(x, y, t)$.

$$\begin{array}{lll} SM(x, y, t) = 1 & if & \begin{array}{c} \left(a < \dfrac{V_{I(x, y, t)}}{V_{B(x, y, t)}} < b\right) \wedge \\ ((H_{I(x, y, t)} - H_{B(x, y, t)}) < \varepsilon_H) \wedge \\ ((S_{I(x, y, t)} - S_{B(x, y, t)}) < \varepsilon_S) \end{array} \\ SM(x, y, t) = 0 & otherwise & \end{array} \quad (6)$$

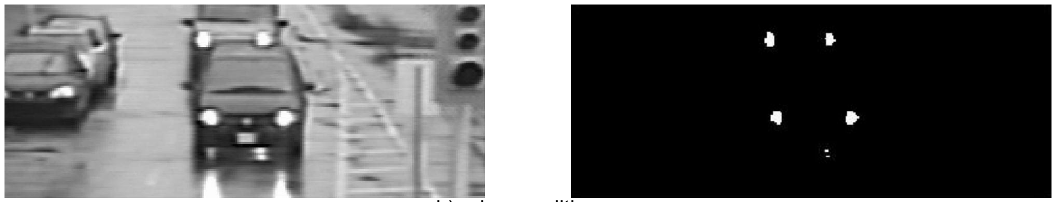
where 0<(a,b)<1 as shadowed areas have lower luminance than the background, and $(\varepsilon_H, \varepsilon_S)$ are kept very small under the assumption that the chrominance of shadowed and non-shadowed areas is similar.

3. EXPERIMENTAL RESULTS

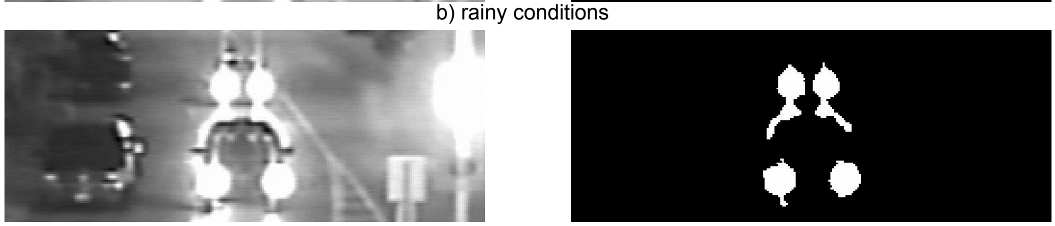
In the context of the application considered in this paper, a fixed camera is installed next to a road intersection and collects image sequences of the traffic. The viewpoint is selected to cover the intersection from above. To improve system performances and to enhance the stability of the application, the field of view of the video camera is to be wide enough to observe all coming vehicles in different lanes from one direction. The goal is to use only one camera per direction of traffic.

This approach has been evaluated on different sequences of real traffic scenes under various weather and illumination conditions. Original traffic images are shown on the left side of

a) sunny conditions



b) rainy conditions



c) at night

Fig. 3. Images and corresponding binary masks under various weather and lighting conditions.

figure 3. The corresponding binary masks obtained with the proposed algorithm are shown on the right side of figure 3. The segmentation results using adaptive background difference and HSV color mapping were stable over a long period of time and compared advantageously with manual segmentation of images for moving objects.

4. CONCLUSION

This paper introduced an approach for the detection of moving vehicles based on color image processing under various uncontrolled weather and lighting conditions. Taking advantage of motion effects and the HSV color mapping the system automatically selects the most salient features under given environmental conditions. The proposed algorithm provided excellent experimental results to detect vehicles arriving at an intersection. The automatic selection of the proper detection mode that allows to switch between a mapping of full vehicle shapes or headlights detection demonstrated very good robustness to diversified environmental conditions. The resulting technology is to be extended to other applications in telesurveillance and telerobotics.

References

[1] A. Soto, A. Cipriano, "Image processing applied to real time measurement of traffic flow", in *Proc. of the Southeastern Symposium on System Theory*, pp. 312-316, 1996.

[2] M. Matsubara, H. Tokutome, K. Nishiyama, M. Aoki, K. Tanaka, "Development of a new multi-purpose image processing vehicle detector and its implementation in the Tokyo Metropolitan Traffic Control System", in *Proc. of Vehicle Navigation and Information Systems Conference*, pp. 95-98, 1994.

[3] H. Hase, K. Miyake, M. Yoneda, "Real-time snowfall noise elimination", in *Proc. of the IEEE Int. Conf. on Image Processing*, vol. 2, pp. 406-409, 1999.

[4] S. Kyo, T. Koga, K. Sakurai, S. Okazaki, "A robust vehicle detecting and tracking system for wet weather conditions using the IMAP-VISION image processing board", in *Proc. of the IEEE/ IEEJ/JSAI Int. Conf. on Intelligent Transportation Systems*, pp. 423-428, 1999.

[5] M. Dufaut, R. Husson, R. Taktak, "Vehicle detection at night using image processing and pattern recognition", in *Proc. of the IEEE Int. Conf. of Image Processing*, vol. 2, pp. 296-300, Nov 1994.

[6] R. Cucchiara, M. Piccardi, P. Mello, "Image analysis and rule-based reasoning for a traffic monitoring system", in *IEEE Transactions on Intelligent Transportation Systems*, vol.1, no. 2, pp. 119-130, June 2000.

[7] M. Tsuchikawa, A. Sato, H. Koike, A. Tomono, “A moving-object extraction method robust against illumination level changes for a pedestrian counting system”, In *Proc. of the Int. Symposium on Computer Vision*, pp. 563-568, 1995.

[8] M. Harville, G. Gordon, J. Woodfill, "Adaptive video background modeling using color and depth", in *Proc. of the 2001 Int. Conf. on Image Processing*, vol. 3, pp. 90-93, 2001.

[9] S. Gupte, O. Masoud, R.P.K. Martin, N.P. Papanikolopoulos, "Detection and classification of vehicles", in *IEEE Transactions on Intelligent Transportation Systems*, vol. 3, no. 1, pp. 37-47, March 2002.

[10] Z. Chunrui, M.Y. Siyal, “A new segmentation technique for classification of moving vehicles", in *Proc. of the IEEE 51st Vehicular Technology Conference*, Tokyo, vol. 1, pp. 323-326, Spring 2000.

[11] R. Cucchiara, C. Crana, M. Piccardi, A. Prati, S. Sirotti, "Improving shadow suppression in moving object detection with HSV color information", in *Proc. of Intelligent Transportation Systems*, pp. 334-339, 2001.