Vehicular Traffic Surveillance for Real Time Using Multiple Methodologies.

Ms. Susmita A. Meshram, Prof. A. V. Malviya

Abstract— Digital image processing is the use of computer algorithms to perform image processing on digital images. As a subcategory or field of digital signal processing, digital image processing has many advantages and applications. One of the applications of digital image processing is for traffic analysis. In literature survey it is found that traffic analysis can be done by Background Subtraction, by non-Drifting Mean-shift using Projective Kalman Filter, using Radar Interferometry. Robust vehicle tracking is essential in traffic monitoring because it is the groundwork to higher level tasks such as traffic control and event detection. The functionality of this technique will be for traffic analysis for real time.

Index Terms—Automotive radar, Computer vision, Kalman Filter, Road vehicle location monitoring, Road vehicle radar, Traffic information systems, Vehicle location monitoring.

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1. INTRODUCTION

A robust vision-based system for vehicle tracking and classification devised for traffic flow surveillance. Traffic monitoring and analysis is essential in order to more effectively trouble-shoot and resolve issues when they occur. The monitoring performs in real time, achieving good results, even in challenging situations, such as with moving casted shadows on sunny days, headlight reflections on the road, rainy days, and traffic jams, using only a single standard camera. Compared with intrusive technologies such as inductive Loop detectors (ILDs), or lasers, computer vision can be used to obtain richer information, such as analyzing the visual features of the vehicles (color, lights, plate number), apart from the geometry (vehicle volume). These advantages and the increasing computational power of processors have made vision-based systems an area of great interest for road operators, particularly in tolling applications [1]. Vehicle tracking has been a focus of attention in the past years due to increasing demand in visual surveillance and security on highways. There have been several techniques proposed for traffic monitoring in the literature based on motion extraction and vehicle tracking. Because monitoring cameras are fixed, background subtraction techniques provide efficient segmentation of motion areas. Background subtraction by mixture of Gaussians is generally used for this purpose [4] [5].

Ms. Susmita A. Meshram. M.E. (DE) Electronics & Telecommunication Department Sipna COET, Amravati (MS) Sant Gadge Baba Amravati University (MS) India.

Prof. A. V. Malviya . Professor Electronics & Telecommunication Department Sipna COET, Amravati (MS)
Sant Gadge Baba Amravati University (MS) India.

2. VARIOUS TECHNIQUES

2.1. Using Markov chain Monte Carlo (MCMC) methods:

For monitoring the vehicle, it performed two kinds of tests: 1) a background subtraction performance to check the sensitivity of our approach to scene variations with respect to recent alternatives and 2) a counting and classification test through a set of videos with different and challenging situations for vision-based systems[1] . The segmentation is further used by a two-step tracking approach, which combines the simplicity of a linear 2-D Kalman filter and the complexity of a 3-D volume estimation using Markov chain Monte Carlo (MCMC) methods[1]. A tracking module provides the required spatial and temporal coherence for the classification of vehicles, which first generates 2-D estimations of the silhouette of the vehicles and then augments the observations to 3-D vehicle volumes by means of a Markov chain Monte Carlo (MCMC) method. Thus, the system reinforces the dark vehicle segmentation and prepares them for a later stage in which the shadow direction will be estimated to reinforce the mask even more [1] [6]. Fig. 1 [1] shows an example of this segmentation procedure. Fig. 2 shows some samples of 3-D tracking result [1].
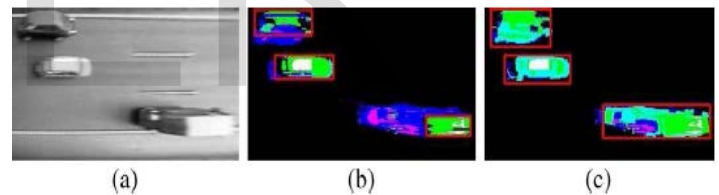

(a) (b) (c)

Fig. 1. Image segmentation results. Image (b) shows the obtained segmentation using the luminance and chromaticity disparity maps only, whereas (c) also includes the gradient cues. The pixel classification colors are background = black, shadow = blue, black = magenta, foreground = cyan, highlight = green, and white = white. It can be observed in (c) how the number of pixels classified as foreground is higher [1].

Fig. 2. Some samples of 3-D tracking result [1].

2.2. Based on mean shift and a projective Kalman filter :

In this, technique the standard Extended Kalman filter implemented on traffic video sequences. The technique proposed is based on motion detection by background subtraction and mean-shift blob tracking. Firstly, the motion image is extracted from the video sequence. Then, the mean-shift algorithm is used to track the blobs through the sequence. Results show that the performance of the standard technique decreases with the number of frames per second whilst the performance of the projective Kalman filter remains constant [2]. This paper proposed a tracking algorithm based on mean shift and a projective Kalman filter. The algorithm achieves robust tracking due to the integration of the projection equation of the vehicle onto the image plane of the CCD camera. In particular, the observation function of the projective Kalman filter models the trajectory of vehicles with respect to their ground distance to the camera. The results showed that both the standard and the projective Kalman filter algorithms achieve robust tracking at a rate of 30fps, even though the projective Kalman filter performs better on long distance vehicles. The observation function projects the physical trajectory onto the CCD plane as shown in Fig. 3[2].
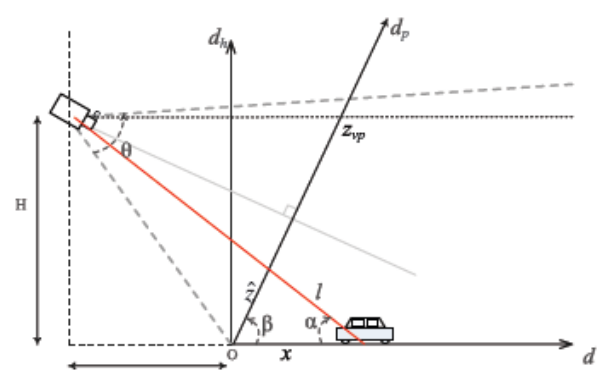

Fig. 3. Projection of the vehicle on a plane parallel to the CCD plane of the camera [3].

The graph shows a cross section of the scene along the direction d (tangential to the road).
Here the trajectories are projected along the tangential
Direction d onto the DP axis, knowing the following "easyto-measure" parameters:
• Angle of view (θ);
• Height of the camera (H); and
• Ground distance (D) between the camera and the first location captured by the camera.

Fig. 4. Background subtraction on a low definition image (128 × 160).
Left is the original image; right is the motion image [2].
Figure 4 displays an image and its corresponding motion mask.

2.3. Using Radar Interferometry :
In next technique, Modern radar systems are able to measure speed and range between vehicle and radar. However, this is not enough to discriminate the lane where the vehicle is driving on. This article explains carefully the operation of the interferometric radar in two configurations: DTR and ATR.

I. DOWN-THE-ROAD CONFIGURATION

In DTR configuration, the axis of transmitting and receiving antennas is directed along the line of travel of the target vehicle.
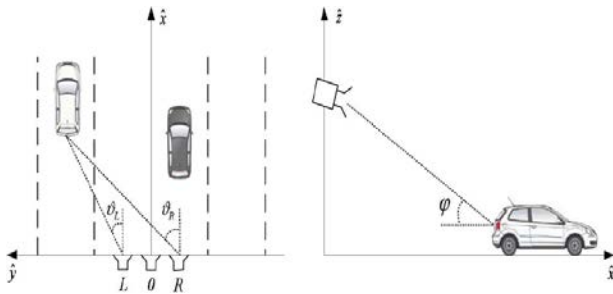

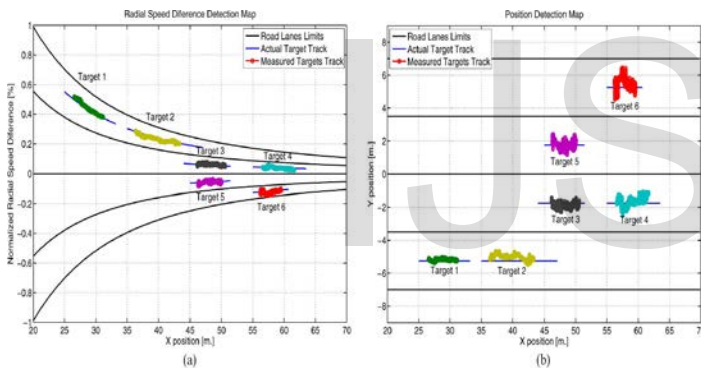Fig. 5. Down-the-road detection geometry.

Fig. 6. DTR detection maps in a simulated scenario. Radial speed difference detection map is shown in (a). Position detection map is shown in (b) [3].

This direction will be the same as the road direction and is represented with the x axis in Fig. 5. with DTR high-resolution radars is that the target response is spread among multiple. Fig. 6 clearly shows many of the reasoning made in Section II-C. Specifically, those related to the width of road lane limits in the radial velocity difference detection map. Furthermore, it can be clearly appreciated how a constant phase difference error in Fig. 6(a) is translated into a higher or lower uncertainty in cross-road measurement depending on target position in Fig. 6(b)[3].

II. ACROSS-THE-ROAD CONFIGURATION

In ATR configuration, the axis of transmitting and receiving antennas is directed across the line of travel of the target vehicle. The direction of the road is represented with the x axis in
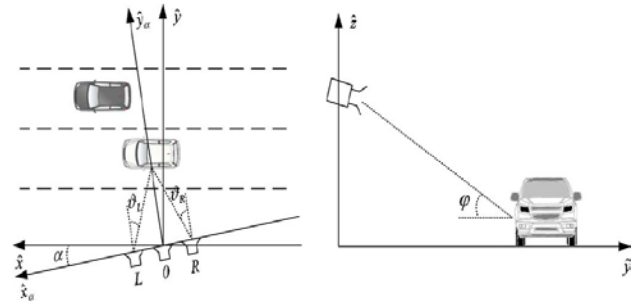
Fig. 7[3].

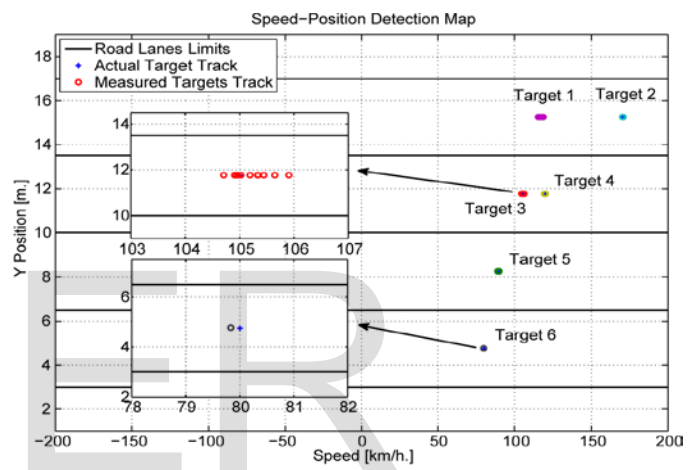Fig. 7. Across-the-road detection geometry.

Fig. 8. ATR simulated scenario and detected targets[3].

A detail of the speed estimation and the road lane detection map are shown in Fig. 8.The limits of the road lanes are plotted in black, the actual target value is plotted in blue, and the detected target value is plotted with a different color for each target[3].

3. CONCLUSION

In this paper we have discussed the different methods for the implementation of vehicular Traffic Surveillance. The first system is a viable alternative to replace ILDs, other technologies such as tags installed in vehicles, laser scanners that reconstruct the 3-D shape of the vehicles, or other computer-vision based approaches, whose installation and maintenance are more cumbersome than using cameras only a novel computer [1]. The another method has presented two different interferometric systems that can simultaneously measure speed, range, and road lane position of several vehicles. In DTR configuration, interferometry is used to estimate road lane posi-

tion [3]. We have discussed a new technique for tracking vehi-
cles with mean-shift using a projective Kalman filter [2].

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