2010 International Conference on Recent Trends in Information, Telecommunication and Computing

Vehicle Detection in Static Images Using Color and Corner Map

R.Aarthi, S.Padmavathi, J.Amudha
Amrita School of Engineering
Coimbatore, India
e-mail:r_aarthi@ettimadai.amrita.edu

Abstract— **This paper presents an approach to identify the vehicle in the static images using color and corner map. The detection of vehicles in a traffic scene can address wide range of traffic problems. Here an attempt has been made to reduce the search time to find the possible vehicle candidates thereby reducing the computation time without a full search. A color transformation is used to project all the colors of input pixels to a new feature space such that vehicle pixels can be easily distinguished from non-vehicle ones. Bayesian classifier is adopted for verifying the vehicle pixels from the background. Corner map is used for removing the false detections and to verify the vehicle candidates**.

Keywords— Color map,corner map,vehicle detection

I. INTRODUCTION

Vehicle detection [1]-[7] is an important problem in many related applications such as driver assisting system, parking identification system. One of most common approaches to vehicle detection is using vision-based techniques to analyze vehicles from images or videos. Due to the variations of vehicle colors, sizes, orientations, shapes, and poses, developing a robust and effective system of vision-based vehicle detection becomes challenging. By addressing the above problem Agarwal and D. Roth [1] defined an approach to deal with still gray images based on part-based representation to represent vehicles. The first stage consists of building a "vocabulary" of parts that can be used to represent objects. Similar parts thus obtained can be grouped together and treated as a single part. In the second stage, each input image is transformed and represented in terms of parts from the vocabulary obtained in the first stage. The pitfall of this approach is the large computational cost. In [2], H. Schneiderman and T. Kanade used a trainable object detector for detecting vehicles at different locations, size and pose. The detector uses multiple classifiers. The disadvantage here is that, an exhaustive scan of the image is required since it uses multiple classifiers. Since it uses eight viewpoints to find all vehicles having different orientations, the time complexity is high. In [4] J. Wu, X. Zhang, and J. Zhou, proposed a system for detecting vehicles from static images based on a pattern classifier built on principal component analysis technique. In [5], A. Bensrhair *et al. presented a stereo vision system for vehicle detection. Compared to the traditional* stereo-vision algorithm, this approach is not aimed at a complete 3D reconstruction but to the mere extraction of features belonging to a vehicle, namely only 3D vertical edges. The disadvantages are that, an unfriendly environment may lead to false detections. A. Broggi, P. Cerri, and P. C. Antonello *[6] described a system for vehicle detection which is based on the search for areas with a high vertical symmetry in static images;* The major flaw with this system is that, not all the detected boundary boxes are correct; some false positives occur due to other objects in the scene like road signs etc.

II. OVERVIEW OF SYSTEM

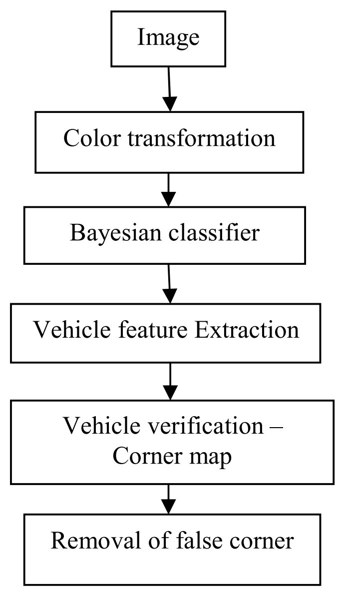


Figure.1. Flow diagram for vehicle detection system

In given image color transformation and bayesian classifier is applied to identify the vehicle pixel from non-vehicle pixels. The extracted color feature further processed to identify the vehicle corners.

III. COLOR FEATURE EXTRACTION

Feature extraction is finds the significant information about an object from large set of data. This helps to avoid redundancy and simplifies amount of resources required to describe an object. It extracts the subset that contains the critical information without much loss in the original data set. Dimensionality reduction is often performed for feature extraction in reducing computational load.

978-0-7695-3975-1/10 $25.00 © 2010 IEEE
DOI 10.1109/ITC.2010.13

The main idea of dimensionality reduction is selecting a subset of features from original data and generating lower dimension data still preserving the distinguishing characteristics. High-dimensional data is often looses without tight clusters. By projecting high dimension data onto an appropriate lower-dimensional space (feature space), data clusters would have a local structure that makes the close neighborhood meaningful. The floor transformation projects all color pixels on a two dimensional feature space. On this feature space, all vehicle color pixels are concentrated on a smaller area.

The color plane (u, v) perpendicular to the axis (1/3, 1/3, 1/3) is given by [7],

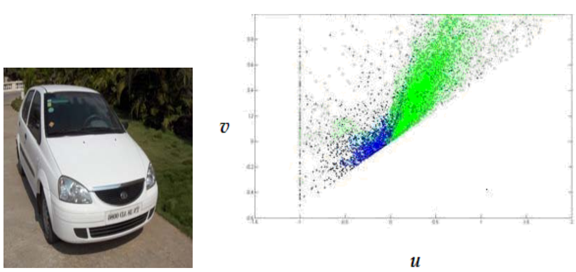
$$u = (2Z - G - B)/Z$$
$$v = \max\{(B - G)/Z, (R - B)/Z\} \quad (1)$$

where $Z = (R + G + B)/3$ is used for normalization and R,G,B are components of color image.Actually, in color image processing for the R,G and B channels, if they are used separately each of them will be prone to false alarms than their composition Z. Therefore, the components B and R are replaced with Z in (1) to reduce the false alarms. The new color transform is given by,

$$u = (2Z-G-B)/Z$$
$$v = \max\{(Z-G)/Z, (Z-B)/Z\} \quad (2)$$

The color transformation in (2) will concentrate all vehicle pixels on a smaller area than (1).

For the image in Figure. 2(a), Equation (2) is used to project all color pixels on the (u, v) space. Then the problem of vehicle detection reduces to a two class separation problem out of which a best decision boundary from the (u, v) space is found such that all vehicle pixels can be separated from the non-vehicle pixels.



(a) (b)

Figure 2 (a) Sample input (b) Result of color transformation using Equation (2)

Vehicle pixel classification using Bayesian rules

The mean colors of the vehicle pixels (m_v) and non-vehicle pixels (m_n) are calculated from the training images in the (u, v) color domain. $\sum_v$ and $\sum_n$ are their corresponding covariance matrices in the same color domain.

According to the Bayesian rule we can assign a pixel '*x'* to the class 'vehicle' if

$$p\,(vehicle/x) > p\,(non\text{-}vehicle/x) \quad (3)$$

Using (3) Non-vehicle pixels can be discarded and the Vehicle pixels are extracted.

IV. Vehicle Features

Vehicles usually contain many corners even though they have different visual changes like orientations, sizes, colors or types. Different vehicles contain variable number of corners. The Harris corner detector is used to extract the corners from any given image (I) as per the following steps,

Step1: Using Sobel operator, the partial derivatives of the image in x and y axes i.e., I_x *and* I_y is calculated.

Step2: Using Gaussian filter as the mask second order partial derivatives of the image in x and y axis is obtained I_x^2 *and* I_y^2 are obtained

Step3: Function M_c is calculated as follows:

$$M_c = I_x^2 * I_y^2 - I_{xy}^2$$

Step4: Local maxima is calculated

Elimination of false corners using Simple Mask Method

Verification is done based on the result of corner detection and it is done to remove false corners. In Simple mask method, a mask of size λ_c is taken and shifted over every detected corners of the image. In every position, number of corners lies with the mask is counted. If the number of corners is greater than λ_c, then the corner belongs to a vehicle. Using the extreme corners the vehicle area is identified and marked with the regular shape. The above sequence of techniques can be used to locate the vehicle candidate in the parking space.

V. Performance Analysis

To evaluate and measure the performance of the system, precision and false-alarm rates are calculated. A database comprising 80 still images was collected. The dimension of the training samples was clipped to 267 * 200. Precision is the ratio of the number of correctly detected vehicle pixels to the number of exactly existing vehicle pixels. False alarm rate is the ratio of the number of background pixels but misclassified as vehicles to the number of all background pixels.

$$\text{Precision Rate} = C_{vehicle} / N_{vehicle}$$
$$\text{Rate of False-Alarm} = F_{vehicle} / N_{back\text{-}pixels}$$

where $N_{vehicle}$ is the total number of vehicle pixels, $C_{vehicle}$ is the number of correctly detected vehicle pixels, $N_{back\text{-}pixels}$ is the number of all background pixels, $F_{vehicle}$ is the number of background pixels misclassified as vehicle ones. The ground truth of vehicle pixels was manually obtained.

The lower false alarm rate implies that most of the background pixels were filtered out and does not need to be further verified. Thus, many redundant searches can be avoided in advance and the verification process can be significantly speeded up to find desired vehicle candidates. The performance of the vehicle detector varies depending upon color of the vehicle. Since the training data set did not have yellow samples, the detection accuracy is minimal. So, by increasing the training samples of different colors we can achieve the better accuracy.

TABLE I. PERFORMANCE COMPARSION AMONG DIFFERENT COLORS OF VEHICLE

Sl.no	Performance Evaluation		
	Vehicle Color	*Precision rate*	*False Alarm Rate*
1.	White	91.73	3.41
2	Metallic Silver	88.26	4.23
3	Black	85.19	6.47
4	Green	83.92	6.84
5	Yellow	79.66	8.33

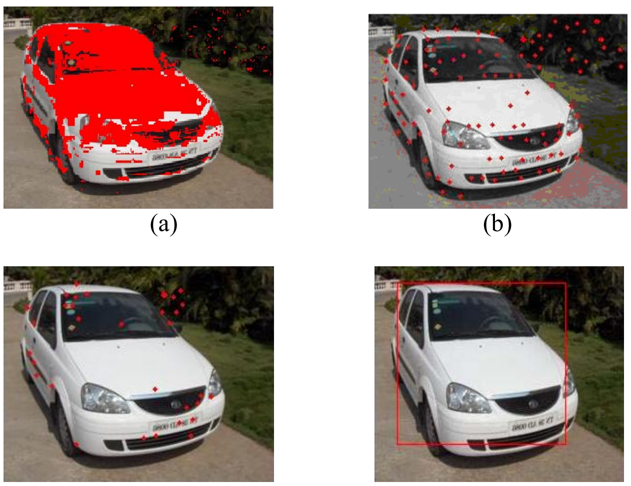


Figure 3. (a) Detection result of color transformation and Bayesian classifier (b) Result of Harris corner detector (c) Result of elimination of false corner (d) Result of vehicle detection

Figure 4. (a) & (b) Result of detecting vehicle in parking space and highway

VI. CONCLUSION

In this paper, we have addressed the issue of detecting vehicles from static images. A color transformation is used to project all pixels of the image onto a 2D feature space such that vehicle pixels form a compact cluster and can thus be easily identified from the background ones. Many redundant vehicle candidates are eliminated in advance using the Bayesian classifier. The detection algorithm holds good for all the vehicles, even with different sizes and orientations. An effective scan is performed to verify all the vehicle candidates. Different from other methods which needs an exhaustive search to find all possible vehicle candidates, this method detects vehicles more quickly and efficiently. This system is robust in dealing with various outdoor images containing different weather and lighting conditions. The average accuracy rate of vehicle detection is 87.2 %.

The performance of the vehicle detector can be improved by adopting an exhaustive training procedure. It can constitute a very large training data set comprising of images with uncommon vehicle colors. A special feature pertaining to vehicle such as height, shape and vertical symmetry can be combined with the color feature so as to eliminate the occlusions of other objects. SVM can be used instead of Bayesian classifier to refine the detection results.

REFERENCES

[1] S. Agarwal and D. Roth, “Learning a sparse representation for object detection,” in *Proc. Eur. Conf. Computer Vision*, May 2002, vol. 4, pp. 113–130.

[2] H. Schneiderman and T. Kanade, “Object detection using the statistics of parts,” *Int. J. Comput. Vis.*, vol. 45, no. 3, pp. 151–177, Feb. 2004.

[3] J. Wu, X. Zhang, and J. Zhou, “Vehicle detection in static road images with PCA and wavelet-based classifier,” in *Proc. IEEE Intelligent Transportation Systems Conf.*, Oakland, CA, Aug. 25–29, 2001, pp. 740–744.

[4] Z. Zhu *et al.*, “Car detection based on multi-*Cues* integration,” in *Proc.17th Int. Conf. Pattern Recognition*, Aug. 2004, vol. 2, pp. 699–702.

[5] A. Bensrhair *et al.*, “Stereo vision-based feature extraction for vehicle detection,” in *Proc. IEEE Intelligent Vehicles Symp.*, Jun. 2002, vol. 2, pp. 465–470.

[6] A. Broggi, P. Cerri, and P. C. Antonello, “Multi-resolution vehicle detection using artificial vision,” in *Proc. IEEE Intelligent Vehicles Symp.*, Jun. 2004, pp. 310–314.

[7] Luo-Wei Tsai, Jun-Wei Hsieh, Kuo-Chin Fan,” Vehicle Detection Using Normalized Color and Edge Map” in IEEE transactions on image processing, vol. 16, no. 3, march 2007