A NOVEL APPROACH FOR VEHICLE DETECTION FOR DRIVER ASSISTANCE

K S Chidanand Kumar[1]

[1]Alumni of Department of E & C, National Institute of Technology, Surathkal, India

chida_imagep@yahoo.in

ABSTRACT

This paper presents a novel approach for detecting vehicles for driver assistance. Assuming flat roads, vanishing point is first estimated using Hough transform space to reduce the computational complexity. Localization of vehicles is carried using horizontal projection on the horizontal gradient image below vanishing point. An uppermost and lowermost peak in the horizontal profile corresponds to search space of vehicles. Binarization of search space on the horizontal gradient image is done using Otsu algorithm. Verification of vehicles is carried through a series of rule based classifiers constructed using statistical moments, observing peaks in vertical profiling, vehicle texture, symmetry and shadow property. Experimentation was carried out on flat highway roads and detection rate of vehicles is nearly found to be 88.23%.

KEYWORDS

Vanishing point, Horizontal projection, Vertical projection, Otsu, Gray Level Co-Occurrence Matrix, Entropy, Homogeneity, Vehicle Gray Scale Symmetry.

1. INTRODUCTION

A lot of risk is involved in driving. Even though modern day technology cannot avoid risk, at least it can reduce the risk. Hence intelligent driver assistance is an active research area among automotive manufacturers with the aim of reducing injury and accident severity. In our research work vision-based vehicle detection is to sense a leading vehicle and thus spontaneously alert a driver of precritical conditions with the front/rear vehicle, in case he/she makes a sudden break, slowdown driving or uniform movement. Sun et al [1] made an overview for vision-based on-road vehicle analysis, which is strictly divided into hypothesis generation and hypothesis verification corresponding to detection and recognition respectively. The hypothesis generation step uses the knowledge, stereo vision and motion based methods. Knowledge-Based method uses many features (symmetry, color [2], shadow, corner, edge, and texture). Bertozzi and Broggi [3] used stereo vision-based method to detect both generic obstacles and lane positions in a structured environment. They utilized Inverse Perspective Mapping technique to remove perspective effect and reconstruct a 3-D mapping when the camera parameters and the knowledge about road are known. The requirement of 3-D transformation and the knowledge of hardware parameters for stereo-based vehicle detection method have highly increased the computational cost and reduced the processing speed. Motion-based methods use motion vectors such as optical flow [4] to locate objects with large displacement but such methods suffer from correspondence problems. Hypothesis verification step is separated into two methods: the template and appearance based method. Template-based methods [5] utilize predefined vehicle template to verify suspected patterns through correlation. However, their performance may decisively rely on the created templates. Appearance based techniques uses features like Haar-like [6, 7] and Gabor [8, 9] cooperated with classifiers like SVM and Adaboost proved to yield a decent performance in

Natarajan Meghanathan, et al. (Eds): SIPM, FCST, ITCA, WSE, ACSIT, CS & IT 06, pp. 39–45, 2012.

DOI : 10.5121/csit.2012.2305

the recent literatures. But the execution time of methods using databases tends too slow to be applied to an embedded system.

To solve the above mentioned problems we use integrated techniques of knowledge based and appearance based model. A novel vehicle localization and detection of preceding and oncoming vehicles is proposed in this paper. Section 2 discusses about the vehicle localization, binarization along with Bounding Box evaluation, Section 3 describes vehicle verification using a series of rule based classifiers. Section 4 discusses simulation results followed by conclusion and references.

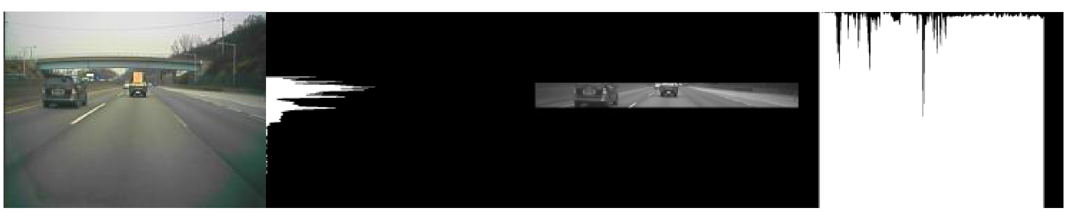
2. LOCALIZATION OF VEHICLES

Localization of vehicles is carried out in three steps. 1) Vanishing point is a point at infinity is first calculated using Hough transform space [10] and need not be calculated for all the frames in a video. To reduce computational complexity, average of first five frames vanishing point is considered as a final position of vanishing point. Segmentation of vehicles is carried out only on the region below vanishing point. 2) Horizontal projection to reduce the search space on the region below vanishing point. 3) Binarization using Otsu algorithm.

2.1. Search space reduction

A vehicle contains strong horizontal lines and this feature is used as cue in segmenting vehicles. In order to get these strong horizontal lines, a horizontal Haar-like feature mask [6, 7] is used. Here the mask size of $9*9$ is used for our experiments. After performing 2D convolution with horizontal Haar-like feature mask, and horizontal projection on the edge image below vanishing point is plotted. A horizontal profile is constructed on the horizontal gradient image which is the sum of horizontal gradient pixel values perpendicular to the x axis and it is represented by the vector P_h of size M rows and defined by:

$$P_h[j] = \sum_{i=1}^{N} S(i, j) \tag{1}$$



(a) (b) (c) (d)

Figure.1

From the Fig.1 (b) horizontal edge profile, it is clear that upper most (U_p) and lower most peaks (L_p) corresponds to regions in which vehicles needs to be searched. Fig.1(c) shows the vehicle localized region. Also a vertical profile is constructed on the localized region obtained from horizontal edge profile. Vertical profile is the sum of vertical gradient pixel values perpendicular to the y axis and is represented by the vector P_v of size N columns and is defined by:

$$P_v[i] = \sum_{j=1}^{M} S(i, j) \tag{2}$$

Also from Fig.1 (d) vertical edge profile, it is observed that minimum peaks corresponds to the region in which in vehicles are located.

2.2. Binarization

Since the vehicle bottom most part in the horizontal edge image appears very strong, the region between (U_p) and (L_p) obtained from vehicle localization process is binarized using Otsu algorithm. Otsu algorithm [11] is a histogram based technique which chooses the threshold such that it maximizes intra class variance. Fig.2 (a) & (b) depicts the horizontal edge image and its binarized image obtained from Otsu algorithm.

(a) (b)

Figure.2

2.3. Bounding Box Evaluation

Bounding boxes obtained from previous binarization process include vehicle baseline edges along with noises like lanes, poles etc. These boxes are passed through a series of rejection filters which rejects unwanted blobs retaining only vehicle blobs using vehicle properties.

2.3.1. Orientation

Since vehicle baseline is almost horizontal, its angle of inclination is evaluated according to the equation below. Order statistical moments as in Equation (2)

$$\theta = \frac{1}{2} a\tan\left(\frac{2M_{xy}}{M_x - M_y}\right) \tag{3}$$

$$M_{xy} = \frac{1}{Area}\sum\sum (X - C_X)(Y - C_y) I(X,Y),$$

$$M_x = \frac{1}{Area}\sum\sum (X - C_X)^2 I(X,Y)$$

$$M_y = \frac{1}{Area}\sum\sum (Y - C_Y)^2 I(X,Y),$$

M_x is the inertial moment relative to Y axis in respect to the center of mass; M_y is the inertial moment relative to X axis in respect to the center of mass; is the inertial moment elative to both X and Y axis in respect to the center of mass, C_x and C_y represent the center of mass coordinates of the binarized bounding box. Also we observed that for a vehicle baseline binarized edge component, $M_x > M_y$ and $M_{xy} = 0$.

2.3.2. Vertical Peaks in Blob ROI

It is observed from vertical edge profile that, there should be two peaks on either sides of the centre of the bounding box of vehicle baseline binarized image. Any blob which doesn't have two peaks on either sides of the centre of bounding box, then those blocks are eliminated.

3. VEHICLE VERIFICATION USING RULE BASED CLASSIFIERS

3.1. Vehicle Texture Property

The GLCM (Gray-level co-occurrence matrix) is a technique in image analysis that is used to estimate image properties related to second-order statistics. GLCM considers the relation between two neighbouring pixels in one offset, as the second order texture, where the first pixel is called reference and the second one the neighbour pixel. GLCM is the two dimensional matrix of joint probabilities $P_{d,\theta}(i, j)$ between pairs of pixels, by a distance d in a given direction θ. Haralick [12] defined 14 statistical features from gray-level co-occurrence matrix for texture classification. In this work, the homogeneity and entropy features are used.

$$Homogeneity = \sum_i \sum_j \frac{P_{d,\theta}(i, j)}{1+|i-j|} \tag{4}$$

$$Entropy = -\sum_i \sum_j P_{d,\theta}(i, j) \log(P_{d,\theta}(i, j)) \tag{5}$$

A blob which passes through 2.3.1 and 2.3.2 weak classifiers, a gray scale region of a blob projected upwards is considered whose height and width is equal to width of a blob. It is observed that for a vehicle, homogeneity value is lower whereas the value of entropy is high.

3.2. Vehicle Shadow feature

Vehicle shadow is used another clue in eliminating Non- ROI‟s. It is observed in the below Fig.3 that vehicle shadow appears as black mask whereas road underneath vehicle appears as a white mask.

(a) (b)

Figure.3

It is observed that for a vehicle, the ratio of sum of pixel values in the black mask to the sum of the pixel values in the white mask should be lesser than 0.6.

$$Vehicle = \begin{cases} 1 & (\sum Black\_ROI / \sum White\_ROI) < 0.6 \\ 0 & Otherwise \end{cases} \tag{6}$$

3.3. Vehicle Gray Scale Symmetry property

Vehicle baseline components obtained from bounding box evaluation process, an ROI is extracted with height and width equal to horizontal width of a component. Vehicle exhibits symmetry property which is used as a cue in eliminating Non-ROI‟s. The gray-level symmetry score is defined as:

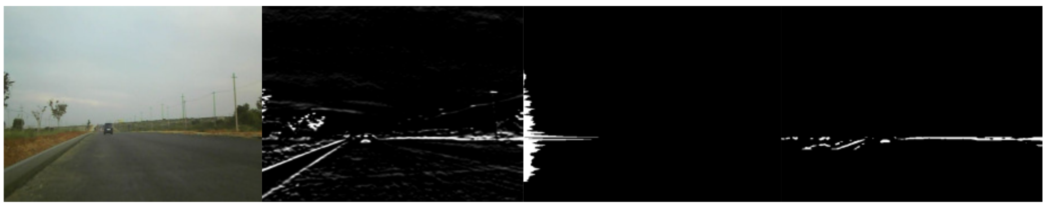
$$Symmetry = \sum_{i=1}^{H} \sum_{j=1}^{W} \frac{|G(W/2-w,h) - G(W/2-w,h)|}{(H*W)} \tag{7}$$

Where $G(x, y)$ is the gray-level value of point (x, y) and H and W denote the height and width of the window, respectively. The higher symmetry value is, the more symmetric the region.

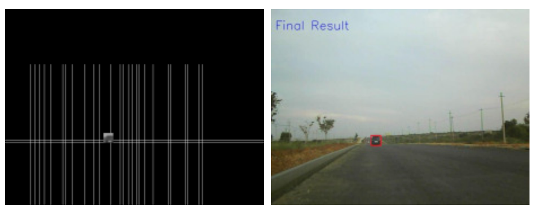
4. RESULTS AND DISCUSSIONS

Figure 4, 5(a)–(f) shows the various stages in detecting the vehicles for driver assistance starting from input image. Vanishing point is evaluated for first five frames of a video. Final vanishing point is the average of first five frames of vanishing point. Segmentation of vehicles is carried only on the region below vanishing point. Figure 4, 5(b) shows the result of 2D convolution of an input image with horizontal edge Haar-like feature mask. Figure 4, 5(c) shows a horizontal projection graph on the region below vanishing point. Figure 4, 5(d) shows the region localized from horizontal projection graph which is considered for binarization process. Figure 4, 5(e) shows the result of binarization process using Otsu algorithm.

Figure 4, 5(f) shows the result of detecting vehicles using a series of rule based classifiers.

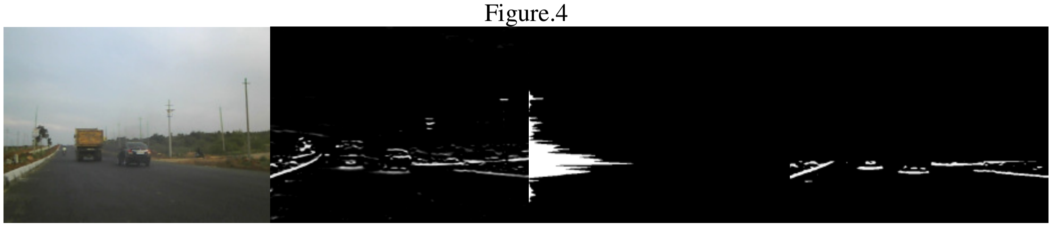


(a) (b) (c) (d)

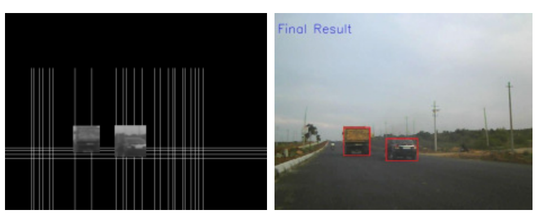


(e) (f)

Figure.4



(a) (b) (c) (d)



(e) (f)

Figure.5

The proposed method has been implemented on Intel Dual Core processor with 1.6GHZ, CPU 256 MB RAM running on windows vista operating system. The program was developed using Visual C++ language and OpenCV2.0. Colour videos of resolution 640×480 are captured on highway roads by mounting the camera on a motor bike. To evaluate the performance of the above proposed approach, we tested with three videos and each video of around more than 2000 frames.

From the Table 1, it is observed for Video 1and Video 2 vehicle detection rate is better than Video 3 because Video 1 & 2 were taken during daytime thereby we can get more strong edges and can be classified easily using a series of rule based classifiers whereas Video 3 is taken during evening time for which it is difficult to have strong horizontal edges and also failure of shadow property.

Table 1. Vehicle detection results

	Video1	**Video2**	**Video3**
Total frames	1000	1000	1000
Hits	1306	740	854
Misses	76	26	164
False positives	13	31	74
% Detection rate	93.62	92.85	78.2
% Average correct rate-88.23%			

5. CONCLUSIONS

The proposed method presents a novel approach for vehicle detection. Vanishing point is first evaluated for first frames of a video. Segmentation of vehicles is carried out only on the region below vanishing point. Search spaces of vehicles are reduced by plotting horizontal projection on the horizontal gradient image. Binarization of search space region is done using Otsu algorithm. Vehicle verification is done using rule based classifiers constructed using statistical moments, texture, vehicle shadow and symmetry property. The vehicle detection using the proposed approach is found to be 88.23%. Future work of this project includes incorporation of current system for Forward collision warning.

REFERENCES

[1] Z. Sun, G. Bebis, and R. Miller, On-road vehicle detection: A review, IEEE Trans. on PAMI, pp. 694–711, May 2006.

[2] J. Rojas, J. Crisman, Vehicle Detection in Color Images, in Proc. IEEE Conference Intelligent Transportation, pp. 403-408, November 1998

[3] M. Bertozzi and A. Broggi, GOLD: a parallel real-time stereo vision system for generic obstacle and lane detection, Image Processing, IEEE Transactions, vol. 7, pp. 62-81, 1998.

[4] J. Wang, G. Bebis, and R. Miller, Overtaking vehicle detection using dynamic and quasi-static background modeling, in Proc. IEEE CVPR, June 2005, pp. 64–64.

[5] A. Bensrhair, M. Bertozzi, A. Broggi, P. Miche, S. Mousset, and G. Toulminet, A cooperative approach to vision-based vehicle detection, in Proc. IEEE Intelligent Transportation Systems, Aug. 2001, pp. 207–212.

[6] P. Viola and M. Jones, Rapid object detection using a boosted cascade of simple features, in Proc. IEEE CVPR, 2001, vol. 1, pp. I–511–I– 518.

[7] P. Negri, X. Clady, S. Hanif, and L. Prevost, A cascade of boosted generative and discriminative classifiers for vehicle detection, EURASIP Journal on Advances in Signal Processing, 2008.

[8] H. Cheng, N. Zheng, and C. Sun, Boosted gabor features applied to vehicle detection, in Proc. IEEE ICPR, 2006, vol. 1, pp. 662–666.

[9] Z. Sun, G. Bebis, and R. Miller, On-road vehicle detection using evolutionary gabor filter optimization, IEEE Trans. on Intelligent Transportation Systems, vol. 6, pp. 125–137, June 2005.

[10] C. C. Wang, S. S. Huang, and L. C. Fu, Driver assistance system for lane detection and vehicle recognition with night vision, in 2005 IEEE/RSJ International Conference on Intelligent Robots and Systems (IROS 2005), 2005, pp. 3530-3535.

[11] R. M. Haralick, K. Shanmugam, and I. Dinstein, Textural Features for Image Classification, IEEE Trans. on Systems, Man, and Cybernetics, 3(6), pp. 610-621, 1973.

[12] N. Otsu. A Threshold Selection Method from Gray-Level Histograms. IEEE Transactions on Systems, Man, and Cybernetics. 1979, 9(1): 62-66

[13] B. E. Boser, I. Guyon, and V. Vapnik. A training algorithm for optimal margin classifier, In Computational Learning Theory, pages 144–152, 1992.

[14] N. Cristianini and J. Shawe-Taylor, Introduction to Support Vector Machines. Cambridge University Press, 2000.

[15] V. Vapnik. The Nature of Statistical Learning Theory. Springer, N.Y, 1995.

Authors

K S Chidanand Kumar born in Mandya, Karnataka, India on 07/12/1981. He received his B.E (Electronics and Communication) in 2003 from VTU Belgaum and obtained his M.Tech (Microelectronics) in 2006 from NIT Surathkal. He is currently working as an Independent consultant. Prior to this he was working in Samsung Electro mechanics as a Senior Software Engineer. His research interests include Digital Image Processing and Pattern Recognition