Proceedings of the 2004 IEEE
International Conference on Networking, Sensing & Control
Taipei, Taiwan, March 21-23, 2004

Vision-Based Driving Environment Identification for Autonomous Highway Vehicles

Yao-Jan Wu
Civil Engineering Department
National Taiwan University
Taipei ,Taiwan
r91521509@ntu.edu.tw

Chun-Po Huang
Electrical Engineering Department
National Taiwan University
Taipei, Taiwan.
d2921003@ee.ntu.edu.tw

Feng-Li Lian
Electrical Engineering Department
National Taiwan University
Taipei, Taiwan
fengli@ntu.edu.tw

Tang-Hsien Chang
Civil Engineering Department
National Taiwan University
Taipei, Taiwan.
thchang@ce.ntu.edu.tw

Abstract – *In this paper, we propose an approach to identify the driving environment for autonomous highway vehicles by means of image processing and computer vision techniques. The proposed approach is mainly composed of two consecutive computational steps. The first step is the lane markings detection, used to identify the location of host vehicle and road geometry. The second one is the vehicle detection that can provide relative position and speed between host vehicle and each preceding vehicle. The proposed approach has been validated in several real-world scenes. Herein, the experimental results indicate low false alarm and low false dismissal and have demonstrated the robustness of the proposed detection approach.*

Keywords: Driving environment identification, Image processing, Computer vision, Lane markings detection, Vehicle detection

1 Introduction

Transportation has been playing an important role in modern society. In the fields of the Advanced Vehicle Control and Safety System (AVCSS), a subsystem of the Intelligent Transportation System (ITS), many efforts have been devoted to prevent accidents by using computer vision techniques [1]-[4]. As a result, the computer vision can be used as a tool to assist people to detect the driving environment around the host vehicle. Therefore, by developing lane markings detection and multiple vehicle detection system on a vehicle can provide more information to driver assistance system, autonomous highway vehicle system, or even collision warning system for decision-making.

For the purpose of identifying the driving environment, it is necessary first to know the precise position of the host vehicle moving on the highway by means of vision-based lane markings detection system. Therefore, 3-dimensional geometry and layout of road can be easily modeled. There are several works has been done in this field [5]-[7]. Meanwhile, vehicle detection procedure not only provides the number of vehicles ahead but also acquires the relative position and speed of each one. In [7]-[10], the authors have employed complex algorithms to comply with the objectives of driving environment identification.

In this paper, we present an approach that effectively and efficiently combines lane markings and vehicle detection for identifying the driving environment in front of the host vehicle. In order to collect the real-time circumstance in front of the host vehicle, a CCD camera is installed on the central top of the dashboard. In the experimental procedure, all the input data and computerized modules are processed in a standard computer system. Moreover, the method proposed can complement any safety decision-making systems such as lane departure system and collision warning system, or just provide the driver the instant and correct information.

2 Lane Markings Detection

In designing an automated driving system in intelligent highway systems, the first task needed is to identify the geometric location of the host vehicle under control and the relative position with respect to other vehicle and objects along the highway. One way to determine the location of the host vehicle is to identify the relative position between the vehicle and the lane markings. By continuously identify the relative position, the vehicle trajectory and other related vehicle variables can be constructed or estimated.

2.1 Define Searching Range

There is too much information contained in one image taken by the camera. If the image sequence is processed directly in real-time, the accuracy and efficiency will not satisfied result. Hence, it is impossible for a computational unit to process all images simultaneously. To overcome this drawback, a searching region of the original image, called region of interest (ROI), is defined in [6]. The ROI is an adjustable range according to the situation of vehicle mounting camera and all the image processing techniques are applied only within the ROI. One sample image with the searching region, ROI, is shown in Figure 1.

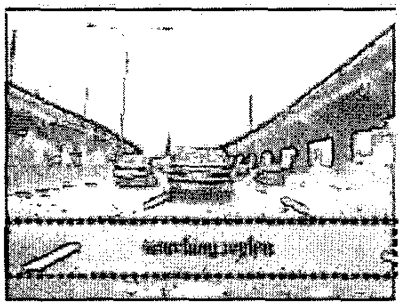


Figure 1: Sample ROI in one grabbed image.

2.2 Make Discrete Lane Markings Continuous

After defining a searching region, the lane markings are identified by image processing techniques. However, the lane markings are discrete in nature; hence, for the purpose of generating one continuous vehicle trajectory, these lane markings should be further processed to form a continuous lane markings. The technique used in the study is to first analyze the position of the possible discrete lane markings distributed all over the ROI. The high-color image *H(t)* and low-color image *L(t)*, with 3 cycles of accumulation are illustrated in Figure 2. The continuation of the discrete lane markings is done by differentiating the images between the accumulated high-color and low-color images.

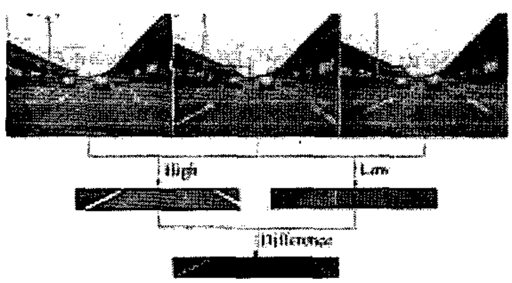


Figure 2: The Continuation of Discrete Lane Markings

2.3 Segmentation

In order to segment the lane and road, a technique called P-tile [13] is used to determine a suitable threshold value for the portion of lane markings. The threshold value P_{th} is the mean value adding one standard deviation of the difference image. Hence, if a normal distribution is assumed, the 67th–percentile value in the gray-level histogram of the ROI is the threshold value. Figure 3 illustrates the gray-level histogram of the difference image in the ROI as shown in Figure 3. A threshold value of 53 is determined by the P-tile method. After the segmentation process, noisy images could appear in the searching region and might affect the correctness of recognizing lane markings. The noisy images could be further removed by the opening technique [12].

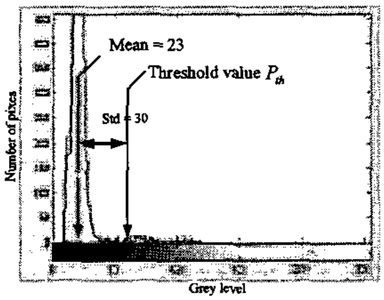


Figure 3: P-tile Method

2.4 Line Fitting

The equations of two lanes, L_r and L_l shown in Figure 4, nearby the host vehicle can then be determined by the information obtained in the segmentation step. The equations are used to find the position of the geographical vanishing point. The equation of the central line, L_c shown in Figure 4, is set as the starting point for every horizontal image scanning both to the left and to the right till the possible locations of left lane markings and right lane markings, respectively, within the ROI. After marking the coordinates of left and right lanes, the least square method is used to construct linear models for the right- and left-lane markings. In this case, the least square method [11] is used to fit a linear model $L(x) = ax + b$. Hence, the two sets of linear equations L_r and L_l could be then determined by using the information of the left- and right-lane coordinates.

2.5 Host vehicle environment building

Using the equation of these two lines, their intersection point *V*, called the vanishing point can be determined. Theoretically, extending all of the lanes on the highway will pass thought the vanishing point. In the study, the widths of all the lanes on the highway are assumed the same, as shown in Figure 4. The information of the point *V*, line L_l, and line L_r can be used to find the width R_w. Furthermore, the equations of all other nearby line markings can be determined by extending the equation of L_l and L_r as shown in Figure 4. Therefore, the geometry of the host vehicle environment can be set and built completely. Moreover, there are several important positions as shown in Figure 4 and described as follows. *P* is the central position of host vehicle, P_c is the central position of lane, P_l and P_r is the closest position between host vehicle and two lanes, and line L_c is the equation representing the central line of lane.

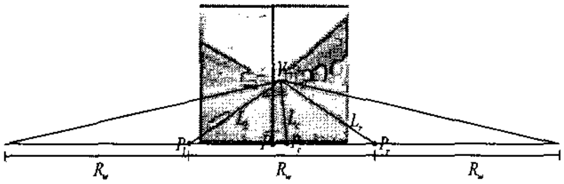


Figure 4: The geometric diagram of the host vehicle environment.

2.6 Identification of lateral distance and speed of the host vehicle

After the host vehicle environment is built, the relationship between the host vehicle position and the center of the lane can be measured by calculating the deviation between the center points P and P_c. The time-varying relative lateral displacement and speed to the central line can be further computed. On the other hand, due to the dynamical movement of the host vehicle, the unpredictable vibration might introduce further uncertainty on the identification of the lateral displacement and speed. To resolve this situation, the α-β filter [13] is adopted first to predict the lateral distance and speed for the next moment, then to decrease the unstable phenomena which is caused by vehicle vibration, and finally to smooth the measured information. The equation of the α - β filter for predicting information is described as follows:

$$d_s(k) = \hat{d}(k \mid k) = d_p(k) + \alpha_d[d_o(k) - d_p(k)] \tag{1}$$

$$v_{sd}(k) = \hat{\dot{d}}(k \mid k) = v_{sd}(k-1) + \frac{\beta_d}{q_d T}[d_o(k) - d_p(k)] \tag{2}$$

$$d_p(k+1) = \hat{d}(k+1 \mid k) = d_s(k) + T \cdot v_{sd}(k) \tag{3}$$

where $d_o(k)$ is the observed relative distance at the kth scan, $d_p(k)$ is the predicted relative distance at the kth scan, $d_s(k)$ is the smoothed relative distance at the kth scan, $v_{sd}(k)$ is the smoothed relative velocity at the kth scan, T is the sampling interval, q_d is the number of scan since the last measurement, and α_d and β_d are the filter coefficients. Figure 5 illustrates the lateral displacement and speed estimated by the result during the α - β filter where the host vehicle executes a lane change maneuver at the 240th second.

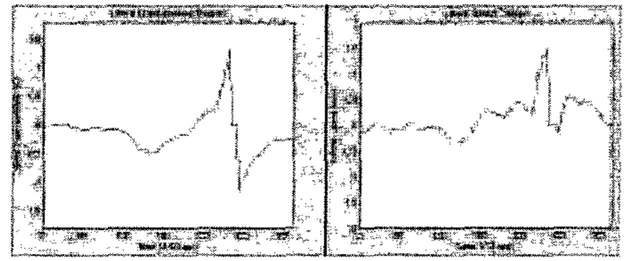


Figure 5: The lateral displacement and speed to central line of the host lane

3 Multiple Vehicle Detection

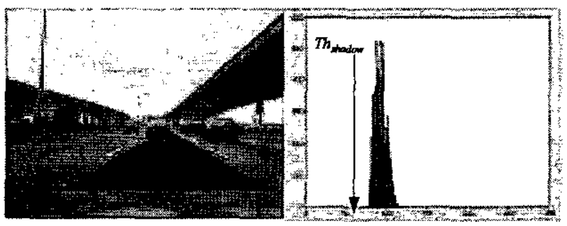
In this section, we discuss the procedure of detecting multiple vehicles on the highway. The goal is to identify the total number of vehicles in front of the host vehicle and the relative distance and speed of the vehicles with respect to the host vehicle. The proposed procedure should first utilize the lane information obtained by the lane markings detection procedure discussed in previous section and then apply heuristic approach to avoid unexpected false alarms in image processing part.

3.1 Pre-processing Step

The raw images captured by the camera usually contain undesired noisy information. Hence, it is required to preprocess the images by applying the Gaussian filter [11] to reduce the influence of undesired factors on the input images. The Sobel filter is then utilized to extract the horizontal edge of the features or objects on the images. The outcome of the Sobel filter with a low threshold value forms a binary "Horizontal Edge Map" where the locations of any horizontal lines will be identified by the algorithms in next subsection.

3.2 Primary Search Step

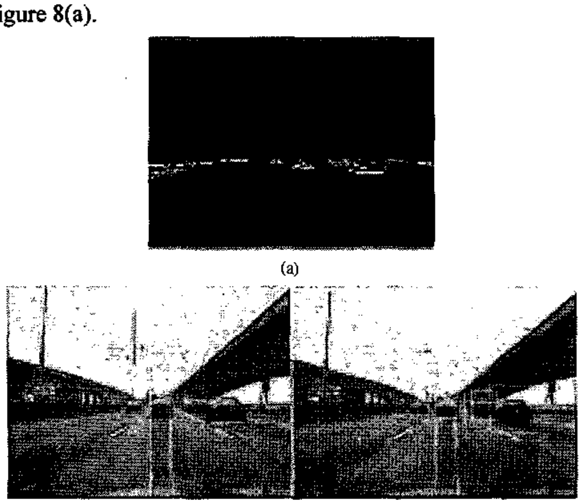
In order to increase the processing efficiency and speed, the possible locations of vehicles in front of the host vehicle are first decided by identifying the regions of the possible shadows underneath the vehicles [8, 10]. The shape of the shadows could be assumed to be horizontal lines. By using the information of lane marking and the property of the vanishing point mentioned in previous section, the region needed to be processed is within a triangular area, called the free-driving space, of these two lane markings and the bottom edge on the image. In order to segment the road and shadow underneath the vehicles in the image, an upper bound of threshold value, namely Th_{shadow}, for the shadow regions should be decided first. The threshold value is calculated based on the statistic within the free-driving space and the histogram of pixels within this region follows a Gaussian distribution with a mean μ and a variance σ. Furthermore, due to the variation of illumination, the threshold is modified by the following equality $Th_{shadow} = \mu - B * \sigma$, where B is the proposed brightness adjustment factor (μ /(number of gray levels)). An example of input image is shown in Figure 7(a) where the dark triangular region is the so-called free-driving space. The histogram of the free-driving space is depicted in Figure 7(b). A Dark Map of only containing "0" and "1" can be further constructed, where "1" indicates the grey-level value of the pixel is below Th_{shadow} and the pixel is regarded as shadow.



(a) (b)

Figure 7: Free-driving-space

By further analyzing the characteristics of the shadow underneath the vehicle, it can be shown that the shadow is usually horizontal and a transition area from light to dark when scanning the image bottom-up. The Horizontal Edge Map and Dark Map are fused together by an "AND" operation to generate a new image containing sparse binary horizontal lines which are the possible places of the shadows underneath moving vehicles. The dots generated by undesired noise are eliminated by binary image processing techniques, e.g. "opening". Note that all image processing steps are done below the horizontal across the vanishing point. This can further reduce the computational complexity of post-processing steps. The result is shown in Figure 8(a).



(a)

(b) (c)

Figure 8: Location of potential vehicles

After all the locations of the potential vehicles are identified, a rectangular region containing one vehicle could be constructed as shown in Figure. 8(b) and 8(c). This region of image will be further processed by the refined search technique discussed in next section to find the contour of the vehicle. Since all vehicles in the image sequence are moving to the Focus of Expansion, or FOE, the size of each outer rectangular region is defined based on the geometrical location of the shadow line underneath the possible vehicle on the image plane and the lane parameters corresponding to the real world. The region possibly containing one vehicle is called a "template" that is used for vehicle tracking tasks in the future.

3.3 Refined Search Step

Focusing on the location of the potential vehicles, the objective in this section is to generate a refined contour inside the aforementioned rectangular region, namely a template, possibly contained a vehicle. It is assumed that most vehicles in the highway have similar rectangular shapes from the front view of the camera-assisted vehicle. Hence the Sobel edge detector is used to find both the horizontal and vertical edges. As illustrated in Figure 9, two histograms by the accumulating the amount of edges corresponding to the vertical and horizontal edges are computed, respectively.

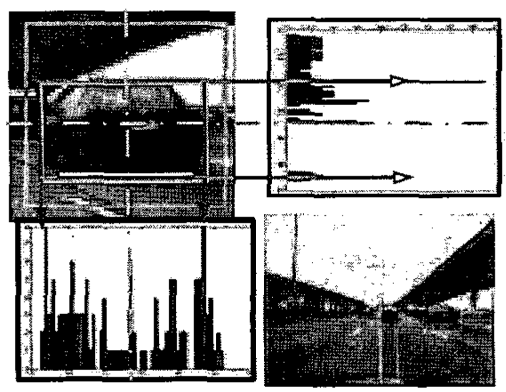


Figure 9: Result of edge detection

The searching process for the edges starts from each side of template to the middle for selecting the larger projection values that indicate the boundary of potential vehicle. The schemes are described as follows:

- For the left boundary of potential vehicle, search from the left to the middle of template and select the projection values above threshold,

$$Th_{left} = \frac{1}{2}\max\left\{Histogram_{V\_edge}(i) \mid 1 \le i \le \frac{n}{2}\right\} \quad (4)$$

- For the right boundary of the potential vehicle, search from the right to the middle of template and select the projection values above threshold,

$$Th_{right} = \frac{1}{2}\max\left\{ Histogram_{V\_edge}(i) \mid \frac{n}{2} \le i \le n \right\} \quad (5)$$

- For the upper boundary of the potential vehicle, search from the top to the middle of template and select the projection values above threshold,

$$Th_{upper} = \frac{1}{2}\max\left\{ Histogram_{H\_edge}(i) \mid 1 \le i \le \frac{m}{2} \right\} \quad (6)$$

- For the lower boundary of the potential vehicle, use the original information obtained from the result in the primary search step.

Finally, the range of the potential vehicle can be determined as shown in Figure 10.

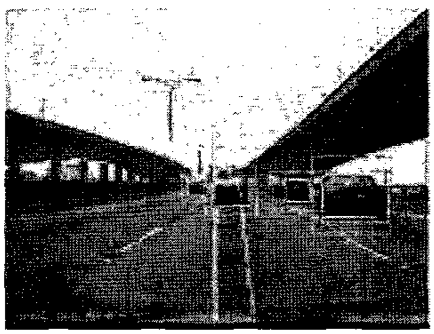


Figure 10. Result of refined search step

3.4 Verification Step

For achieving the robustness of the overall processing system, it is further verified that the template actually contains one vehicle after the contour of potential vehicle is decided. The parameters used for verification are described as follows:

- Aspect ratio: Depending on the configuration of the camera, a threshold is defined for the aspect ratio (ratio of the width to height of the inner enclosing rectangle);

- Texture: According to the information theory, the entropy is used as a measure to estimate the uncertainty so as to check whether a vehicle is contained in the enclosing rectangle. If the enclosing rectangle contains no vehicle, it indicates that it contains little information and the entropy is low. The entropy is determined by the following formula:

$$H(z) = -\sum_{j=1}^{J} P(a_j)\log P(a_j) \quad (7)$$

where $P(a_j)$ is a probability distribution and $J = 255$ is the gray scale.

- Symmetry: The symmetry property of regular vehicles is computed by evaluating the difference between the right- and left-half of inner enclosing rectangle.

3.5 Construction of driving environment

After successfully detecting all vehicles in front of the host vehicle, the relative position (D_x and D_y) can be calculated based on the information obtained by the lane geometry and the vision system with exact calibration performed in advance. Furthermore, the position of the host vehicle corresponding to the host lane in the real world can be also determined, as shown in Figure 11. Finally, the driving environment of the host vehicle can be completely constructed.

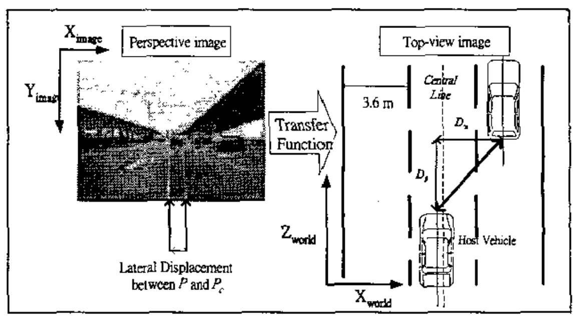


Figure 11: Identification of driving environment

3.6 Experimental Results

The vehicle detection algorithm has been tested in more than 10 scenarios of video clips captured in daytime. As shown in Table 1, the method is evaluated by the statistic of error rate. Herein, the error rate is composed of false alarm rate and false dismissal rate. Of course, the error rate is proportional to the number of vehicle appearing in the image sequences.

Table 1: Experimental results of vehicle detection

Video clip	(1)	(2)	(3)
Freeway 1	25/293 = 8.5%	40/293=14%	4/293=1.3%
Freeway 2	20/344 =5.8%	62/344=18%	7/344=2.0%
Freeway 3	4/275 = 1.4%	55/275=20%	5/275=1.8%
Freeway 4	44/452 = 9.7%	78/452=17.3%	10/452=2.2%
Freeway 5	2/221=0.9 %	10/221 = 4.5%	2/221=0.9%
Average	6.0%	15.5%	1.8%

(1)False alarm rate (Number of False alarms/ Total frames), (2) False dismissal rate within a range of 100m

(Number of False dismissals / Total frames), (3) False dismissal rate within a range of 30m (Number of False dismissals / Total frames)

As shown in Table 1, the vehicle detection algorithm performs well with low false dismissal rate within short range. Furthermore, in terms of initializing a tracking process, the proposed algorithm causes few false alarms that would lead the system to spend meaningless time for tracking non-vehicle targets.

4 Conclusion and Future work

In this paper, we first presented an effective approach to detect the lane markings correctly and to construct the driving environment of the host vehicle by lane information. The information can be further processed for deriving the driving trajectories of the host vehicle that could be used to reflect the vehicle behavior on the highway.

As for vehicle detection, we proposed a four-step procedure that effectively integrates lane information and vehicle parameters to minimize the computational complexity and to achieve high detection performance. The experimental results revealed that the average false dismissal rate within a short range is lower than 2%. Moreover, the proposed method will be suitable for identifying the environmental situation and complementing any forward collision warning system or other safety decision-making systems.

In order to guarantee the performance and robustness of the proposed approach, vehicle tracking techniques should be included in the future post-processing steps. Moreover, these proposed algorithms will be integrated with vehicular and environmental monitoring as well as automatic driving system to achieve the ultimate goal of fully autonomous highway systems.

Acknowledgement

This work is partially supported by the National Science Council, Republic of China, under grants NSC 92-2211-E-002 -091-

References

[1] T. H. Chang, C. H. Lin, C. S. Hsu, and Y. J. Wu, "A Vision-Based Vehicle Behavior Monitoring and Warning System." Proceedings of the IEEE 6th International Conference on Intelligent Transportation Systems Shanghai, China, pp.448~453., October 2003.

[2] Chiung-Yao Fang, "A Vision-Based Driver Assistance System Based on Dynamic Visual Model. Ph.D dissertation. Department of Computer Science and Information Engineering, National Taiwan University, 2003.

[3] Narayan Srinivasa, "Vision-based Vehicle Detection and Tracking Method for Forward Collision Warning in Automobiles," Intelligent vehicle Symposium, IEEE, Vol. 2, pp. 626-631, 2002.

[4] Yen, "Motion Analysis of Nearby Vehicles on a Freeway," Master thesis, Department of Information & Computer Education, National Taiwan Normal University, 2003.

[5] Massimo Bertozzi, Alberto Broggi, Alessandra Fascioli, and Amos Tibaldi, An Evolutionary Approach to Lane Markings Detection in Road Environments, In Atti del 6 Convegno dell'Associazione Italiana per l'Intelligenza Artificiale, pages 627-636, Siena, Italy, September 2002.

[6] S. G. Jeong, C.S. Kim, D.Y. Lee, S.K. Ha, D.H. Lee, M.H. Lee, and H. Hashimoto, "Real-time Lane Detection for Autonomous Vehicle," Proceedings of IEEE International Symposium on Industrial Electronics, Pusan, South Korea, June 12-16, 2001, vol. 3, pp. 1466 –1471.

[7] M.Bertozzi,A.Broggi," GOLD: a parallel real-time stereo vision system for generic obstacle and lane detection, "Image Processing, IEEE transaction on image processing, Vol.7, No.1 pp. 62 -81, Jan. 1998

[8] Christos Tzomakas, W. von Seelen." Vehicle Detection in Traffic Scenes Using Shadows," Internal report IR-INI 98-06, Institut fur Neuroinformatik, Ruhr-Universitat, Bochum, Germany 1998.

[9] M. Betke, E. Haritaoglu, and L. S. Davis, "Real-Time multiple vehicle detection and tracking from a moving vehicle," Machine Vision and Applications: An International Journal, Vol. 12, No. 2, pp. 69-83, September. 2000.

[10] Marinus B. van Leeuwen,Frans C.A. Groen," Vehicle Detection with a Mobile Camera," In submission of Transactions on Pattern Analysis & Machine Intelligence.

[11] Linda G. Shapiro, George C. Stockman, " Computer Vision," Prentice Hall, Upper Saddle River NJ, 2001.

[12] Ramesh Jain, Rangachar Kasturi, and Brian G. Schunck, "Machine Vision," McGRAW-Hill International Editions, 1995.

[13] S.S. Balckman," Multiple-Target Tracking with Radar Applications," Norwood, MA: Artech House, 1986.