Proceedings of International Conference on Image Processing and Character Recognition

Edge-Based Detection of Structured Road Boundaries for Autonomous Land Vehicle

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Abstract

In this paper, a vision scheme with feature-oriented image processing is proposed for structured road boundaries detection. Two criteria are adopted to select the candidates of road boundary edges. The first criterion is the interested range of edge direction and the other one is the minimum size of connected road edge pixels for the local continuity of road boundary. The noises, which can not satisfy the two criteria simultaneously, will be eliminated after performing the proposed image processing. For detecting a segment of anticipated road boundary, our vision scheme decides an area-of-interest subimage and a set of goal-driven parameters as the inputs of the feature-oriented image processing. The extracted boundary in the image is then represented by a straight line segment and used to update the road model. Experimental results show that this vision scheme is successful in detecting the road boundaries under various road environments, even with heavy interference, shadows, and changing illumination due to weather conditions.

1. Introduction

Sensing of surrounding environment is indispensable to the autonomous vehicle, since the vehicle has to drive by itself. Just like human drivers, the autonomous land vehicle requires vision as the major way of sensing to recognize its road environment. There are various types of roads and the definition of road is not unique. It is difficult for a road detection algorithm to cover all types of roads. In this research, we focus our study on the detection of structured road boundaries. The structured road is a well-constructed road of which the road region/boundary can be easily recognized by sight (e.g., the road with painted lane markings, or the road separated by division islands). The proportion of the structured roads in our current world is high.

This work was supported in part by the National Science Council under Grants NSC84-2212-E194-004 and NSC85-2612-E194-012, and by an equipment fund from National Chung-Cheng University in 1994~1995.

Many road boundary detection algorithms have been proposed. Some of them detect the lane markings[1-7], but cannot take care of rural roads that do not have painted line. Some address the boundary detection problem on the road edge without lane markings[8-11]. These methods perform well for simple road environment but not for situations with moderate noises or shadows.

In contrast to the direct road boundary extraction by road edges, region-based approach finds the shape and location of road surface in the image. In general, region segmentation technique is used for gray-level image[12,13], and the pattern recognition technique divides the pixels of a color road scene into road and nonroad classes[8, 14-18]. As the region-based methods do not rely on the road boundary edges, they can be good for detecting unstructured road. Yet for the structured road cases, the processes of the region-based methods are usually more complex and time-consuming, as compared with the direct road edge extraction. The study of region-based approach on structured road detection is thus excluded in this paper.

Investigating the edge-based methods surveyed above, most of them are found capable of detecting road boundary under light noise. Although some methods can deal with heavy interference, they are mainly for painted boundary line tracking and relies much on the previous road model[5,6]. Different features have been proposed for road edge extraction. The use of magnitude and orientation of edge pixels is popular. The orientation of edge pixels can be compared with the predicted road direction from the previous road model[3,5,9,10]. Yet this is not sufficient to extract the road edge pixels correctly, especially under heavy noise. Similarly, the location of edge pixels detected in the previous input image can be used as a feature. The precision of the predicted model and the variation of road boundary in the image sequence are the main factors affecting the performance. In addition, the curvature and length of edge-tracking segment have been used as the extraction feature[11]. Yet this will fail if the road boundary is obscured by other objects.

In our research, by observing the characteristics of structured roads, two discriminating features for the road boundary edges can be noted: (1) The direction of a road boundary edge is limited within a range, as long as the vehicle is roughly heading along the road direction and the curvature of road boundary is not too large. (2) The edge pixels of a road boundary should be with local continuity. That is, the road boundary edge pixels can be linked together to form a continuous line or curve segment, even if the road boundary is partially obscured by the other objects. Based on the above insight, a vision scheme for detecting boundaries of structured roads is proposed. Its detailed implementation and feature-oriented image processing are presented in the following sections.

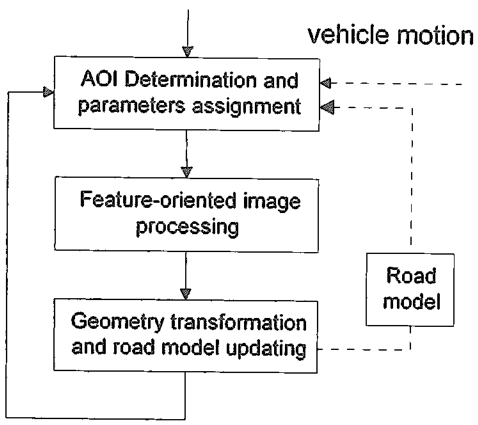

Fig. 1 The configuration of proposed vision scheme

2. Vision scheme overview and road model

The proposed vision scheme is composed of three parts as depicted by the configuration diagram shown in figure 1. The first part in the system is the area-of-interest (AOI) determination and parameters assignment for image processing. The area-of-interest focuses the searching of road boundary on a portion of the input image, so that the image processing can be reduced. The AOI determination is, based on the previously extracted road boundary together with the visual field change caused by the executed vehicle motion, to estimate the approximate location of the road boundary in the subsequent image. And a set of goal-driven parameters are specified for the extraction of either the right-side or the left-side road boundary in our road model. The AOI subimage and the assigned parameters are the inputs for the feature-oriented image processing which uses the discriminating features and the goal-driven parameters to extract road boundary in the AOI subimage. The extracted road boundary is then geometrically transformed for road model updating.

The considered road model consists of the left and right road boundaries. All representations in this model is in three-dimensional space with respect to the vehicle-centered (camera) coordinate system. Each of the road boundaries is represented by a straight line,

$$x\cos\theta + y\sin\theta = d, \qquad (1)$$

which lies on the road plane. Figure 2 gives an illustration of the model. Z_v is the projection of visual direction of the camera and plane Z_v-X_v lies on the road plane. The parameters (θ_r, d_r) and (θ_l, d_l) give the position and direction of the right-side and left-side road boundaries, respectively. This representation of straight line avoids the infinite value when the line is represented by its tangent.

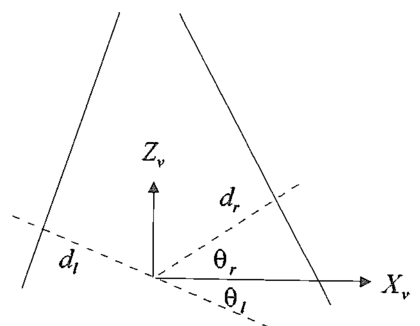

Fig. 2 Road model

The CCD camera is mounted above the road plane in a fixed height but does not aim in parallel with the road plane. The segment of extracted road boundary in the AOI subimage is also represented by the parameters (θ, d) with respect to the two-dimensional image coordinate system. It is then projected onto the road plane by inverse perspective projection for road model updating.

3. Feature-oriented image processing

In a complex and heavily interfered road environment, the edges in the input image are produced by various objects including road boundaries, painted lines, shadows from trees or buildings, cracks or leaves on the paved road surface, and other vehicles. Our approach uses discriminating features to distinguish the road boundary edges from other noisy edges. Based on the features, the edge pixels must satisfy some criteria to become the candidate of road boundary for straight line fitting. The first criterion is the interested range of edge direction. The second criterion is the minimum size of connected road edge pixels for the local continuity of road boundary.

The edges which are produced by other objects have the characteristics of irregular direction and immethodical distribution. They can not satisfy the two criteria simultaneously and will be eliminated after performing the proposed feature-oriented image processing.

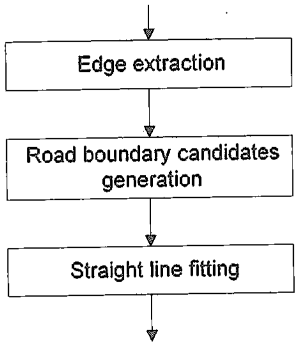

Fig. 3 Three stages of feature-oriented image processing

There are three successive stages in the algorithm as shown in figure 3 :

1. edge extraction,
2. road boundary candidates generation, and
3. straight line fitting.

When an image is acquired from the camera, a portion of the image which is the area of interest is provided as the input of the algorithm. A set of goal-driven parameters are given to guide the algorithm for extracting desired road boundary. Stage 1 extracts the edge magnitude and direction by using two-dimensional gradient operation, and then focuses on the edge direction by the constraint of minimum edge magnitude. Stage 2 attempts to filter an interested range of edge direction for the main features such as the right-side road boundary. Then group the edge points of interested range based on the property of local continuity to eliminate the direction-irregular and distribution-immethodical noisy pixels. Stage 3 fits those road boundary candidates into a straight line by using weighted Hough transform. The line segment in the AOI is transformed back to the original image coordinate system. The detailed steps of each stage are described in the following.

3.1 Edge extraction

By using a two-dimensional 3x3 Sobel operator[19], an image S_1 of which each pixel represents the direction of edge point (for those whose gradient magnitude is greater than a threshold) can be generated. The edge orientation resultant from the spatial gradient varies from -90 to 90 and is linearly transformed to the range, from 0 to 180, for pixel-gray-level representation. It is defined as

$$\theta(i,j) = \deg\left(\tan^{-1}\left(\frac{S_y(i,j)}{S_x(i,j)}\right)\right) + 90\,, \tag{2}$$

where S_x and S_y represent the gradient magnitude of x and y direction, respectively. The image S_1 is obtained by

$$\begin{aligned} S_1(i,j) &= \theta(i,j), \qquad \text{if } S_m(i,j) \ge T\,, \\ &= 0\,, \qquad \text{otherwise,} \end{aligned} \tag{3}$$

where S_m is the gradient magnitude, and T is a threshold which is chosen as 80 empirically in our experiment. The value of threshold is not the determinant factor for the success of entire processing. Figure 5(b) shows an example for the processing result at this stage.

3.2 Road boundary candidates generation

Based on the criterion of edge direction, filter the edge image with specific range of edge values for the desired road boundary. The noises caused by other objects will become fewer in its amount and topological disconnection, because of its irregular edge direction. The remaining noise edges look like pepper-and-salt in the noise-reduced image. Let θ_s and θ_e are the parameters which are previously given and denoted as starting and ending angles for the interested range of edge direction. Thus the noise-reduced edge image S_2 can be obtained by

$$\begin{aligned} S_2(i,j) &= S_1(i,j), \quad \text{if } \theta_s < S_1(i,j) < \theta_e \\ &= 0\,, \qquad \textit{otherwise.} \end{aligned} \tag{4}$$

For our road model, the edge direction of the right-side road boundary is in the range from 0 to 90 without prediction. Using the parameters θ_s=0 and θ_e=90, the right side of road boundary candidates can be extracted. The direction-filtered edge image is shown as figure 5(c) and 6(c) corresponding to without prediction and with prediction, respectively. Similarly, let θ_s=90 and θ_e=180, the algorithm can be used to find the left side of road boundary.

The criterion, which is the minimum size of connected edge pixels for the local continuity of road edges, helps to eliminate the rest of pepper-and-salt noises for extracting the road boundary candidates. Use four-connected neighborhood grouping technique to cluster the individual region, and then filter out the region whose area is less than a threshold. The road boundary candidates are then clearly extracted.

Applying four-connected neighborhood grouping operation[19], the noise-reduced edge image S_2 can be classed into individual regions $\{R_m\}$ by assigning the same code in the same region. It is a two-pass operation.

In the first pass, each pixel is assigned a code m which belongs to the region R_m. The second pass is to merge the pixels with different codes but in the same region. This results an image whose pixel value represents the region code to which the pixel belongs. Count the area $\{A_m\}$ for all grouped regions and filter out the region whose area is less than a minimum value A_{min}. Thus, we can get the road boundary candidates image S_3. If the number of grouped regions is equal to zero, than the algorithm reports no road boundary found.

The choice of parameter A_{min} is dependent on the noisy interference. The choice of A_{min} is not the deterministic factor for the success of the algorithm. Thus the suitable value is not a fixed but a range of value. In our experiment, A_{min} is chosen as 30 empirically. Figure 5(d) and 6(d) show the grouped regions after the criterion of minimum area.

Since we prefer to find the one-pixel-wide road edge, it is not worth to apply thinning algorithm to the S_3. Instead of using thinning algorithm, a simple search to find the one-pixel-wide road boundary edge is adopted. The method is to scan each row in S_3 from left to right for finding the first visited pixel of each region. Thus we get the image S_4, which still contains the information about individual regions. The steps are

1. For each row j of S_3, initialize a list of mask $M[N]$ for all regions, where N is the number of grouped regions.
   $M[k]=0$, $k=1$ to N,
   $M[0]=1$,
   where region 0 represents the background pixel.
2. Scan the row from left to right. if $M[S_3(i,j)]$ is equal to 1, then let $S_4(i,j)=0$, otherwise set $S_4(i,j)=S_3(i,j)$ and $M[S_3(i,j)]=1$.
3. Repeat steps 1-2 until all rows are scanned.

The one-pixel-wide road boundary edge images are shown in figure 5(e) and 6(e).

3.3 Straight line fitting

Straight line fitting is achieved using weighted Hough transformation. The fitted straight line is represented by $x \cos\theta + y \sin\theta = d$ with respect to image coordinate system in AOI subimage. Each of candidates is projected into a set of points in the Hough parameter space by varying θ from starting angle to ending angle. The dimension of the Hough parameter space is $(\theta_s - \theta_e) \times (2\sqrt{w^2+h^2})$, where w and h are the width and height of the image. The weight given by the parameter assignment is employed to dominate the increment of the voting for the road boundary extraction. The increment is dependent on the weight and the angle which is the prediction of road boundary direction appeared in this AOI. The voting increment is decided by

$$increment = \mathrm{int}\left(\left(1 - \frac{|\theta - \theta_p|}{90}\right)W\right) + 1, \tag{5}$$

where θ is the angle of voting pixel, θ_p is the prediction of road boundary direction which is the intermediate angle of starting and ending angles, and W is the weight of increment.

The weighted increment for parameter space voting improves efficacy of the straight line fitting than the traditional method. An angle near the predictive direction of the straight line gains greater increment in its voting than one far from that. The weight is assigned to zero when there is without any prediction of road boundary. The weighted Hough transform is degraded into a traditional one.

After the voting of all edge candidates for a specific range of edge direction, the maximum vote in the parameter space is selected for the straight line. The straight line fitted to the edge candidates is represented as (θ, d). Figure 5(a) and 6(a) show two examples for W=0 and W=5 respectively.

4. Geometry transformation and road model updating

Usually, a segment of straight line can be found through the image processing in the AOI subimage. The model of the straight line, (θ, d), is related to the coordinate system of AOI subimage. For the inverse perspective projection, it needs (θ_{new}, d_{new}) defined in the coordinate system of entire input image. The transformation of (θ, d) is given by follows.

$$\theta_{new} = \theta, \tag{6}$$

$$d_{new} = d + p_x \cos\theta + p_y \sin\theta, \tag{7}$$

where (P_x, P_y) is the upper-left corner of the AOI subimage. The purpose of inverse perspective projection of the road boundary is to obtain the distance from the vehicle to the found road boundary, and to obtain the differential angle between the vehicle head direction and the found road boundary. The detailed discussion can be referred to [20]. Then, a piece of road boundary extracted from the AOI subimage is used to update the current road model based on the parameters assigned.

5. AOI determination and parameters assignment

The AOI determination is based on two factors, the vision processing mode and road boundary type. The vision processing can be applied in two modes: bootstrap and feedforward. The bootstrap mode is exerted when the vision scheme takes its first view of road image or any prediction about the road boundary location is not available from the previous results. It usually requires processing of the entire image. Once the road model is created, the vision scheme can predict the location of the road boundaries in the current view and so restricts the processing to a portion of the image. After then, the system operates in the feedforward mode. This kind of processing helps the vision scheme to extract the road boundaries more accurate and fast. For our proposed system, the road model consists of the left and right road boundaries. The AOI is also dependent on which the road boundary is to be detected.

The AOI is represented by four arguments, (p_x, p_y, d_x, d_y). (p_x, p_y) denotes the coordinates of the top-left corner with respect to the original visual image. The parameters d_x and d_y are the width and height of the AOI, respectively. The parameters assignment for feature-oriented image processing is also based on vision processing mode and road boundary type. There are three arguments needed to be assigned. W is the weight of increment used in the straight line fitting. θ_s and θ_e denote the interested range of the expected road boundary direction in the AOI. Their usage in our algorithm is described according to the vision processing mode.

5.1 Bootstrap mode

In the bootstrap mode, the position and direction of the road boundaries are not available. The AOI subimage is selected to cover the entire road plane image. Because of the fixed mount angle between the camera's visual direction and the road plane, the road plane image is always below a fixed row to which the vanishing line projects. In general, the road is not infinitely long, the visual end of the road surface is always below the row. The AOI is thus the subimage which is below the row with a constant offset e. That is

$$p_x = 0,\ \ p_y = v_y + e,$$
$$d_x = w,\ \ d_y = h - v_y - e. \qquad (8)$$

Process the subimage does not only reduce the processing time but also pays attention to find the road boundary in the road plane.

The parameter W for image processing is assigned to zero so that it forces the weighted Hough transform to perform the same as the traditional one. The interested range of edge direction is set as θ_s=0 and θ_e=90 for right-side road boundary, θ_s=90 and θ_e=180 for left-side road boundary.

In our experiment, the acquired visual image is 256x240 in size. The fixed row of vanishing line is 30. We assign the offset e to 10. Thus the subimage contained the road plane is 256x200 in size. Figure 5(a) shows the AOI subimage which is enclosed by a bright box in the bootstrap mode.

5.2 Feedforward mode

With the road boundary obtained in the last image, the location of road boundary can be predicted by combining previously tracked road model and the visual change caused by the vehicle motion. Only the subimage which the predicted road boundary projects to will need to be processed for extracting the road boundary. Let the projected location of the road boundary, either right-side or left-side, in the current image be represented by (θ, d). The AOI can be calculated from (θ, d) and v_y+e. Note that there is a safe margin in determining the AOI subimage for the toleration of inaccurate prediction. It is illuminated as figure 4.

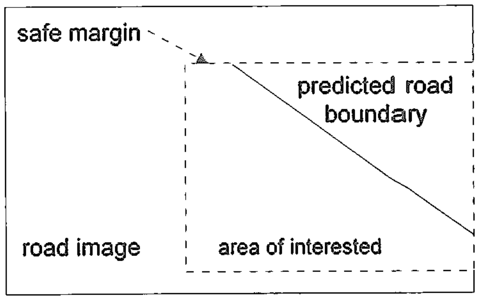

Fig. 4 Area of interested by prediction

The choice of the safe margin should be greater than zero. It is dependent on the capability of road boundary prediction by navigation system. The more precise the prediction is, the less the safe margin requires.

The parameter W for feedforward mode is assigned to 5. The interested range of edge direction is centered at the prediction direction of the road boundary with a constant extend D. Thus they are defined as $\theta_s = \theta_p - D$ and $\theta_e = \theta_p + D$.

6. Experimental results

Several structured road images with difficult road environment and changing illumination of weather condition are processed by the proposed vision scheme for extracting the road boundaries. The results are shown in figure 5 to 7. The vision scheme successfully uses the focus of attention on a portion of input image for a piece of desired road boundary searching, and exploits two discriminating features to distinguish the road edges with noises caused by other objects. Figure 5 and 6 show the visual processes in which how the road edge candidates are distinguished from the heavy interference, in the bootstrap and feedforward mode, respectively.

The feature-oriented image processing is applied to find the road boundary under either simple or complex road environment. It succeeds as well under changing illumination due to weather conditions. Figure 7 shows the examples in the bootstrap mode including heavy shadows caused by trees under sun shine, wet road surface after rain, cracks or stains or leaves on the road surface.

The vision scheme is implemented on SUN SPARC 10 workstation in our experiment. The execution time of vision scheme for a processing cycle is averaged 0.77 second in the bootstrap mode. After the road model is created, the average executing time is reduced to 0.49 in the feedforward mode. It speeds up 57% with respect to the bootstrap mode.

7. Conclusion

A vision scheme with feature-oriented image processing algorithm has been developed for structured road boundaries detection under difficult road environment and changing weather conditions. Based on the proposed discriminating features, two criteria are successfully used to distinguish the significant road boundary edges from the noises caused by other objects. A road model which consists of both the right and left road boundaries is created by straight line fitting. The straight-line model is simple in its few parameters representation and easy implementation for the prediction. The experimental results show that the algorithm does not only specialize in detecting the road boundaries under complex environments, but also keeps the adaptability for the simple road environments.

This feature-oriented image processing algorithm can be used for both the bootstrap and feedforward modes by specifying the AOI and parameters. Although this algorithm performs well, it models the road only as two straight lines. The challenge in the future work is to modify the road boundary representation as second-order polynomials in the world coordinate system.

References

[1] A. Suzuki, N. Yasui, N. Nakano, and M. Kaneko, "Lane recognition system for guiding of autonomous vehicle," in *Proc. Intell. Vehicle Symp.*, 1992, pp. 196-201.

[2] S. Tsugawa, "Vision-based vehicles in Japan: machine vision system and driving control systems," *IEEE Trans. Industrial Electronics*, vol. 41, no. 4, 1994, pp. 398-405.

[3] R.A. Lotufo, A.D. Morgan, E.L. Dagless, D.J. Milford, J.F. Morrissey, and B.T. Thomas, "Real-time road edge following for mobile robot navigation," *Electronics and Comm. Eng. J.*, vol. 2, no. 1, 1990, pp. 35-40.

[4] A.D. Morgan, E.L. Dagless, R.A. Lotufo, D.J. Milford, J.F. Morrissey, and B.T. Thomas, "Image processing for robot road following," in *Proc. Third Int. Conf. Image Processing and its Applications*, 1989, pp. 421-425.

[5] H. Schneiderman, and M. Nashman, "A discriminating feature tracker for vision-based autonomous driving," *IEEE Trans. Robotics and Automation*, vol. 10, no. 6, 1994, pp. 769-775.

[6] C. Thorpe, M. Hebert, T. Kanade, and S. Shafer, "Toward autonomous driving: the CMU Navlab," *IEEE Expert*, vol. 6, no. 4, 1991, pp. 31-42.

[7] K. Kluge and C. Thorpe, "Representation and recovery of road geometry in YARF," in *Proc. Intell. Vehicles Symp.*, 1992, pp. 114-119.

[8] J.-P. Liu, et. al., "The road segmentation for ALV navigation," in *Proc. Int. Conf. Intelligent Robots and Systems:* Advanced Robotic Systems and the Real World, vol. 2, 1994, pp. 974-979.

[9] L.S. Davis, T.R. Kushner, J. Le Moigne, and A.M. Waxman, "Road boundary detection for autonomous vehicle navigation," *Opt. Eng.*, vol. 25, no. 3, 1986. pp. 409-414.

[10] A.M. Waxman, J.J. LeMoigne, L.S. Davis, B. Srinivasan, T.R. Kushner, E. Liang, and T. Siddalingaiah, "A visual navigation system for autonomous land vehicle," *IEEE J. Robotics and Automation*, vol.3, no. 2, 1987, pp. 124-141.

[11] Broggi, A., "Parallel and local feature extraction: a real-time approach to road boundary detection," *IEEE Trans. Image Processing*, vol. 4, no. 2, 1995, pp. 217-223.

[12] X. Yu, S. Beucher, and M. Bilodeau, "Road tracking, lane segmentation and obstacle recognition by mathematical morphology," in *Proc. Intell. Vehicles Symp.*, 1992, pp. 166-172.

[13] G. Funka-Lea, and R. Bajcsy, "Vision for vehicle guidance using two road cues," in *Proc. Intell. Vehicles Symp.*, 1992, pp. 126-131.

[14] M.A. Turk, D.G. Morganthaler, K.D. Gremban, and M. Marra, "VITS - a vision system for autonomous land vehicle navigation," *IEEE Trans. Pattern*
hine Intell., vo

[15] D. Kuan, G. Phipps, and A.-Chuan Hsuen, "Autonomous robotic vehicle road following," *IEEE Trans. Pattern Anal. Machine Intell.*, vol. 10, no. 5, 1988, pp. 648-658.

[16] J.D. Crismán, and C.E. Thorpe, "UNSCARF-a color vision system for the detection of unstructured roads," in *Proc. Int. Conf. Robotics and Automation*, vol.3, 1991, pp. 2496-2501.

[17] C. Thorpe, M. H. Hebert, T. Kanade, and S.A. Shafer, "Vision and navigation for the Carnegie-Mellon Navlab," *IEEE Trans. Pattern Anal. Machine Intell.*, vol. 10, no. 3, 1988, pp. 362-372.

[18] J.D. Crisman and C.E. Thorpe, "SCARF: a color vision system that tracks roads and intersections," *IEEE Trans. Robotics and Automation*, vol. 9, no. 1, 1993, pp. 49-58.

[19] D. Ballard and C. Brown, *Computer Vision*, Prentice-Hall, 1982.

[20] Y.H. Leu, A visual navigation system for autonomous vehicle in the Chung-Cheng university campus, Master Thesis, Institute of Electrical Engineering, National Chung Cheng University, 1994.

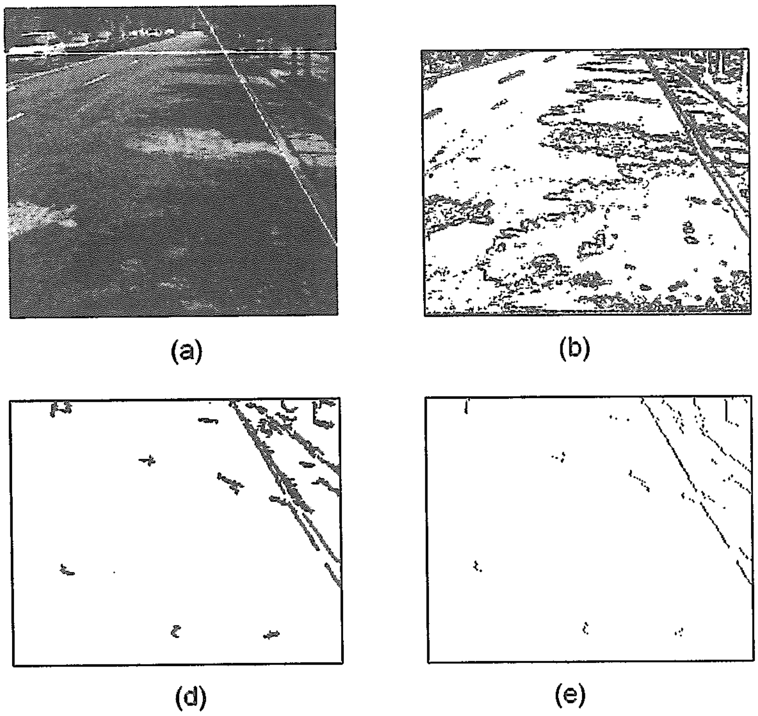

Fig. 5 The processing results in the bootstrap mode.

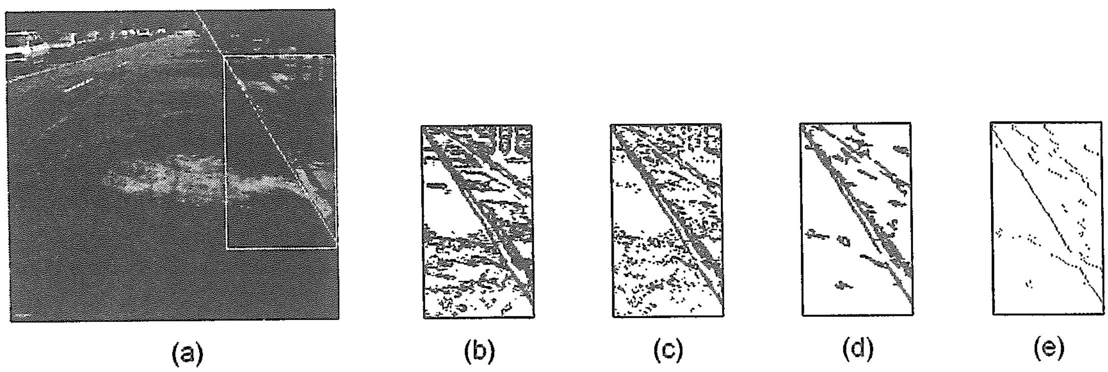

Fig. 6 The processing results in the feedforward mode.

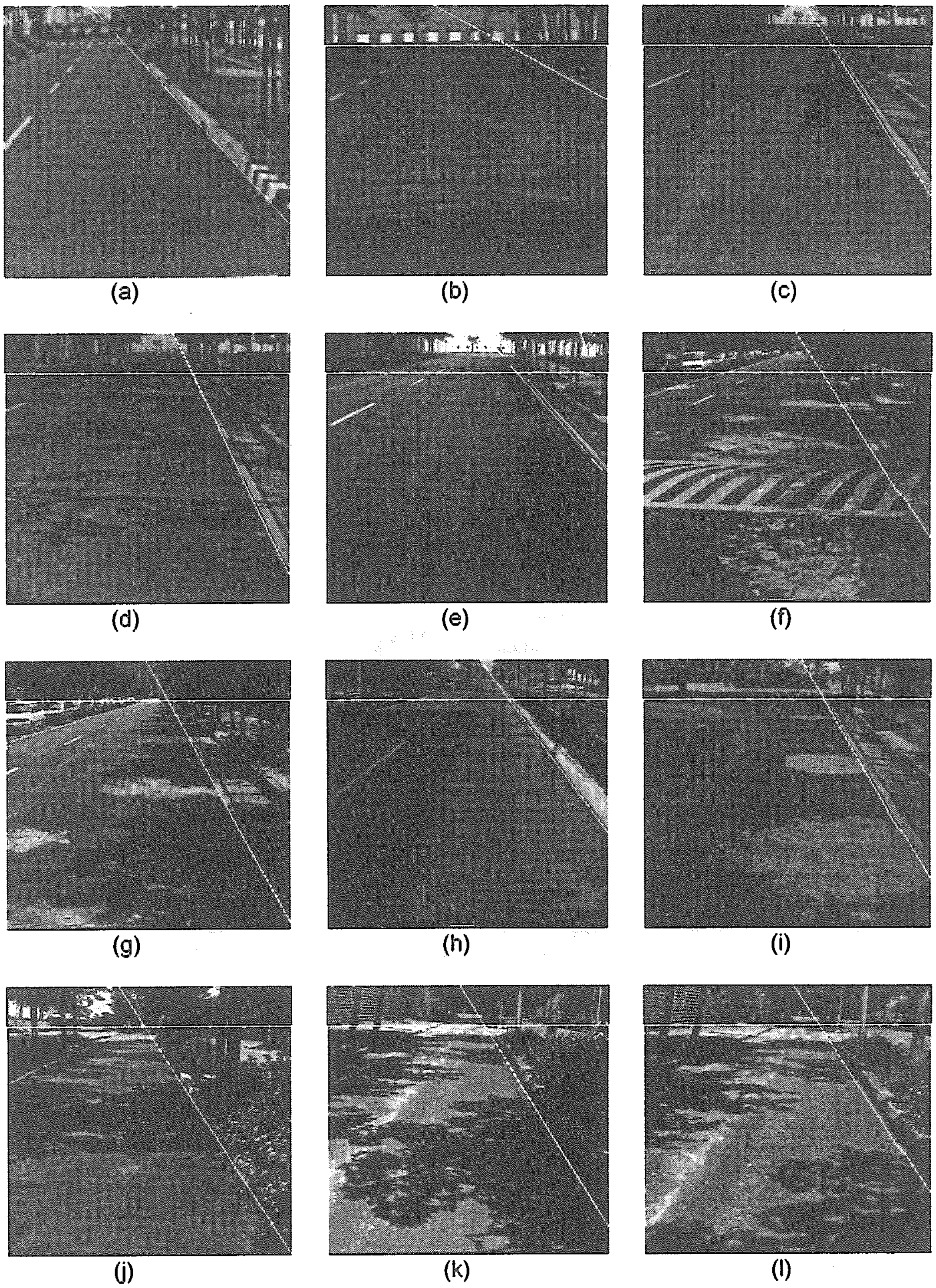

Fig. 7 Experimental results of the right-side road boundary detection under various road environments based on bootstrap mode.