Effective Edge-Based Road Lane Detection

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Abstract – In this paper, an edge-based road lane detection algorithm is proposed. It can detect the centerline of each lane in a road with multiple lanes. This algorithm employs an edge-based approach for extracting edge features of lane markings, kerb and other wayside objects and discriminates useful and unwanted edges in terms of their orientation and length with the aid of 2D-3D coordinate transformation through a camera model, and *K*-means clustering. This method enables edge features with strong orientation and length affinity to retain and cluster, while short and isolated edges are eliminated. Those remaining edges define the lanes and kerbs, from which the centerlines of the lanes can be determined. Overall, the merits of this algorithm are that it is computation efficient, it works on single or multiple lanes and the centerlines it produces are accurate enough to be useful for visual surveillance purposes.

1. Introduction

There has been considerable research interest in intelligent transportation systems (ITS) in the past decade. Road lane detection is one of the requirement that is necessary in almost all vision-based ITS applications. Visual surveillance system can provide the largest volume of information in the most unobtrusive way amongst different surveillance system. It is reputed to be able to measure a large category of parameters such as travel time, speed, incident verification, volume, safety, emissions, weight and class [1], through the used of road-side or overhead mounted video cameras and image processing techniques. To achieve this, certain knowledge of the road direction must be available, and therefore detecting the road lanes or their centerlines naturally becomes an integral part of the whole surveillance process.

The goal of lane detection is to locate the centerline of each lane from a multi-lane digital road image. To achieve this goal, lane markings are often used as the basis for differentiating the road from other features such as trees, bushes, human and others that may possibly be in the image. The major difficulties in detecting the lane markings are that lane markings are not always clearly visible due to changes in environmental conditions; and the numerous types of lane marking could be confusing to any algorithms trying to identify them. The problems of the road splitting or merging within the image and the interference from wayside objects or shadows could also increase the difficulty in detecting the centerlines successfully.

Broadly, the road lane problem has been challenged by many researchers recently and can be roughly classified into region-based [2-5] and edge-based methods [6-8]. Schaaser and Thomas [2] employed a region-based method to segment road markings. Road markings are linked together and are approximated by second orders quadratic curves that described the road boundaries. Their method seems lack of flexibility and the modeling and linking delays increased exponentially with the number of dashed markings per lane boundary, making it rather inefficient in dealing with highways or roads with many lanes.

Weber et al [3] modeled lane boundaries as constant curvature segments by fitting a constant curvature conic section onto a thresholded region using a least square criterion. This method was used for road following where road markings were detected within these segments. Like most road following algorithms, it can only detect one lane. Frank [4] outlined similar color classification methods to separate road and non-road pixels in the image through a trained neural network. The direction of the road is obtained by analyzing the shape of the road markings. Those objects with shapes that do not fall into the category are discarded. In this method, the accuracy of the road marking detection relies heavily on the local threshold and the contrast of the images. As a results some of the non-road marking objects failed to be discarded. Thorpe et al [5] proposed a different region-based approach for road detection in their Navlab. They assumed that the road has no road markings at all. Image pixels are classified into road and non-road pixels according to their colors, based on known road colors. Naturally, any change in outdoor illuminations may change the road colors perceived by the camera and introduce errors in the classification. This method was applied to a road image with good contrast between the road and the wayside objects. As it is, it does not recognize multiple lanes either.

Kasprzak et al [6] presented a road parameter estimation method which classifies edges into three classes. Vanishing point is used to define the horizontal ground. Edges above the horizontal ground are eliminated while edges below the horizontal ground are further classified as road and non-road edges. The stability of the algorithm seems to be highly dependent on the vanishing point detection while the accuracy of the detection is generally low and depending on the image sequence. Campbell and Thomas [7] also employed edge detection for road following in their paper. The detected edges of the road markings are transformed from the 2D image coordinates into 3D coordinates based on a calibrated camera model, after which the road is modeled by six parameters. These parameters are updated from frame to frame based on an initial guess. As it is, the update process seemed to be time consuming with slow convergence. The final detection of the road marking can be reasonably accurate depending on the initial guess. Kluge and Lakshmanan [8] described a deformable template approach that is based on image intensity gradient. A likelihood function was used to provide a relative measurement of how well a given set of shape parameters matched the pixels. The algorithm uses an iterative method in which given sufficient number of iterations have been performed, the detected road matches closely with the actual road. However, the number of iterations required to achieve this can be up to 703,000 as mentioned in their paper.

In this paper, an effective edge-based road lane detection algorithm is proposed. It can detect the centerline of each lane in a road with multiple lanes. Without loss of generality, road lanes are assumed to have strong orientation and length affinity. The algorithm utilizes this assumption with the prominent features of the road markings and kerb structures. It employs an edge-based approach for extracting edge features of lane markings, kerb and other wayside objects. As useful and unwanted edge features are both detected, the resulting edges are discriminated against their orientation and length with the aid of 2D-3D coordinate transformation through a camera model, and *K*-means clustering. This method enables edge features with strong orientation and length affinity to retain and cluster, while short and isolated edges are eliminated. Those edge lines with strong orientation and length features define the lanes and kerbs, from which the centerlines of the lanes can be determined. Overall, the merits of this algorithm are that it works on a single image and is computation efficient. It also works on single or multiple lanes and the centerlines it produces are accurate enough to be useful for surveillance purposes. Furthermore, its orientation and length discriminations are robust through the use of *K*-means clustering.

This paper is organized as follows: Section 2 gives an overview of the proposed algorithm; Section 3 briefly describes the edge detection; Section 4 discusses the camera model being used in the 2-3D coordinate transformation; Section 5 details the heuristics used for orientation and length discrimination; Section 6 describes the lane analysis; and the paper is concluded in Section 7.

2. Overview of the Algorithm

The proposed algorithm is based on edge detection, and also utilizes the kerb information as well as the orientation and length affinity between edges. Fig. 1 depicts the conceptual diagram of the proposed road lane detection algorithm. The road image may be acquired from a still or video camera. For still images, it has to be taken when there is no vehicles on the road. For videos, background estimation [9] can be applied if there are vehicles on the road. Noise corruption due to acquisition or transmission can be removed by one of

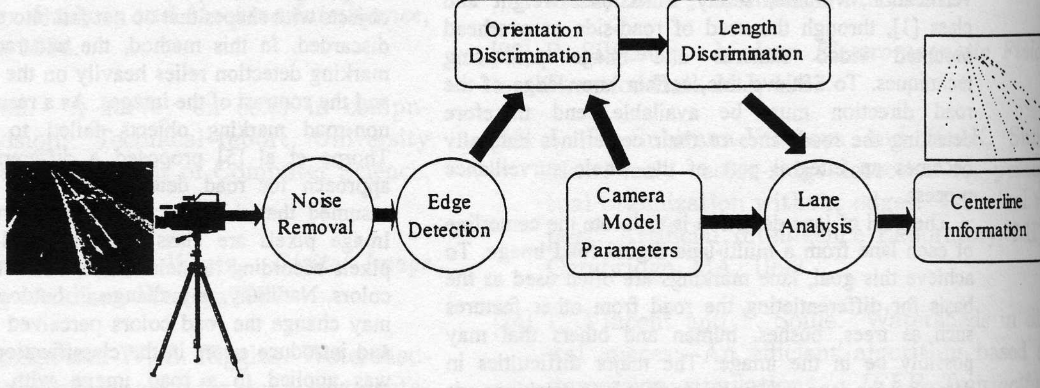


Fig. 1 – Conceptual diagram of the proposed lane detection algorithm

the feature preserving filtering algorithms [10,11]. Feature preservation is essential here as conventional filters blur the image and reduce the edge detection accuracy.

After noise removal, the edge detection process extracts edge information in the usual sense, from which edge pixels are thinned and then approximated by straight lines where each line has an associated orientation and length. These edge lines are then clustered according to their orientation and length using the *K*-means clustering technique [12]. The orientation clustering is performed in the 3D coordinate through a 2D-3D coordinate transformation based on the camera model. This enables the edge lines in the 2D perspective view to be transformed into 3D coordinates which can be viewed from above. As edges due to wayside objects, uneven road color or surfaces, or noise, are usually short and dissimilar in orientations, they can simply be discarded. Besides, road sections usually have constant width and the edge lines defining these sections are usually long and appear to be in parallel when viewed from the top in 3D. This simplifies the lane analysis process and further discriminates those lines that do not describe the lanes or lines. If any of the road marking or kerb features are missing, the other one can be relied upon. Our experimental results show that it is likely that the lines describing the road marking are hard to detect. From the parallel lines describing the lanes or road, centerlines can be calculated as the arithmetic mean between two adjacent lines. This solution is obviously not suitable for road images with sharp bends or roundabouts, where edge lines describing the road would have large variation in orientation. However, for straight roads and roads with a slight curvature, the solution works well.

3. Edge Detection

In general, there are a number of features that can be

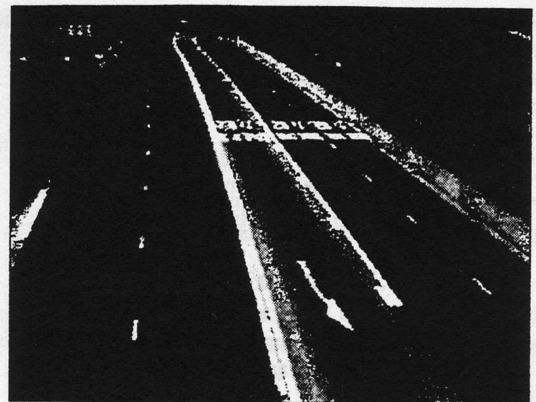
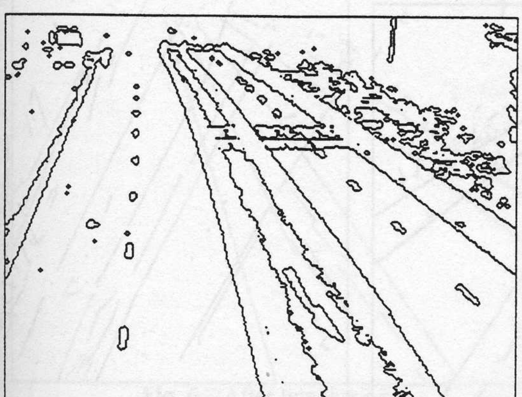


Fig. 2 – A typical road image

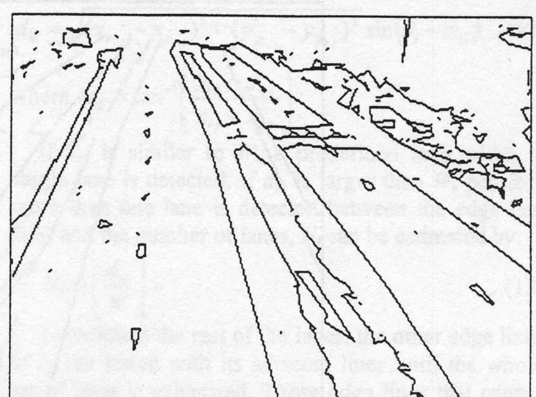
found on a road as depicted in Fig. 2. These features consist of various types of lines in white or yellow defining lanes and separating traffic. Road signs such as direction arrows and instructions painted on the road can sometimes be seen as well. In addition, slightly elevated kerb structures are common fixtures, separating the other wayside objects such as bush, trees, grass, lamp-posts and buildings from the road. Therefore, the role of the edge detection here is to extract these prominent features in a reliable fashion.

The selection of a suitable edge detector for this purpose must be based on its accuracy to extract the features, rather than its ability to ignore wayside objects. For this reason, the Sobel edge detector was chosen for its differencing and smoothing properties [13], together with medial-axis transformation to generate a one-pixel thick edge map as shown in Fig. 3(a). The edge pixels are then linearly approximated into straight-line segments as depicted in Fig. 3(b).

Mathematically, the gradient is approximated by $|G_x|+|G_y|$ where both values are defined in the usual sense, and the set of edge lines, *E*, extracted from an



(a) Thinned edge map



(b) Straight line approximated edge map

Fig. 3 – Edge maps of Fig. 2

image I, can be described as a collection of straight lines

$$E = \{e_k = (p_{k,h}, p_{k,t}) : p_{k,h}, p_{k,t} \in I \mid k = 0,\ldots,N-1\} \quad \ldots(1)$$

where $e_k = (p_{k,h}, p_{k,t})$ denotes a line segment defined by two points $p_{k,h}$ and $p_{k,t}$, and N is the number of edge lines in the set.

4. Camera Model

The camera model depicted in Fig. 4 describes the transformation of the image coordinates into real-world coordinates and vice versa.

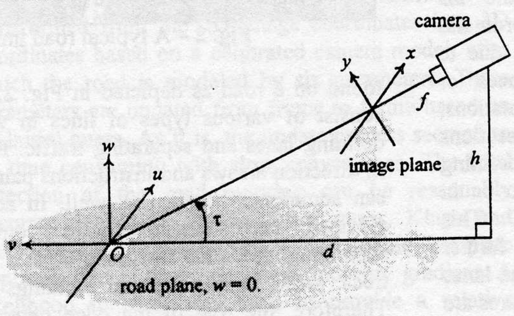


Fig. 4 - Camera model

In this model, the road is assumed flat and the camera is mounted at a height of h and focused at O, which is lying on the w=0 plane, with focal length f, while the distance between O and the camera is d and the elevation angle is τ. The road surface is defined to be coincide with the $w = 0$ plane. Based on this camera model, the transformation, Φ, of a point, $p(x, y)$, from the 2D image coordinates to a point, $P(u, v, 0)$, in the 3-D real-world coordinates may be defined as:

$$P(u, v, 0) = \Phi\{p(x, y)\} \quad \ldots(2)$$

where

$$\begin{cases} u = x \cdot \sqrt{\dfrac{(d+v)^2 + (h-w)^2}{f^2 + y^2}} \\ v = \dfrac{y \cdot [d^2 + h \cdot (h-w)] - f \cdot d \cdot w}{h \cdot f - d \cdot y} \end{cases} \quad \ldots(3)$$

Since the road is on the w=0 plane, Eq. (3) can be simplified to

$$\begin{cases} u = \dfrac{x \cdot h \cdot \sqrt{d^2 + h^2}}{h \cdot f - d \cdot y} \\ v = \dfrac{y \cdot (d^2 + h^2)}{h \cdot f - d \cdot y} \end{cases} \quad \ldots(4)$$

5. Edge Discriminations

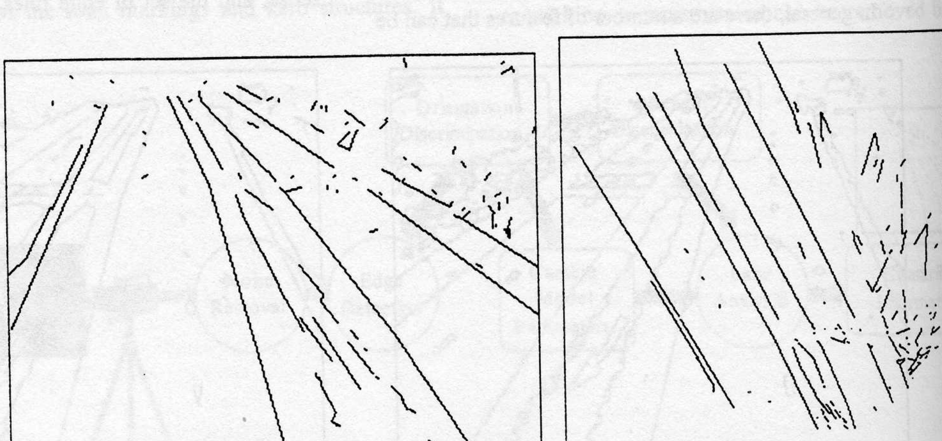
5.1 Orientation Discrimination

Let us first define a road lane to have the following characteristics: locally flat, defined by parallel road markings or kerb lengthwise and without sharp bends or roundabouts. Other than these, a road can consist of only one lane or multiple lanes. For orientation discrimination, let the orientation, Θ, defines a set of edge lines as given by

$$\Theta = \{\theta_k = \angle e_k : \theta_k \in [0 \ldots \pi) \mid k = 0,\ldots,N-1\} \quad \ldots(5)$$

where $\theta_k = \angle e_k$ denotes the orientation of an edge line e_k in the 3D coordinates and is bounded between 0 and π. Consider the length of each line e_k to be defined by $|e_k|$, for each orientation θ_k, we can obtain a length value, L_{θ_k} representing the sum of the length of all the edge lines having the same θ_k, as given by

$$L_{\theta_k} = \sum |e_i| \quad \text{for all } \angle e_i = \theta_k \quad \ldots(6)$$



(a) Edge map in 2D

(b) edge map in 3D

Fig. 5 – After orientation discrimination

As this is carried out in the 3D coordinates, parallel lines defining road markings and etc. have large L_{θ_k}, while other edge lines give small L_{θ_k}. We then apply the *K*-means clustering with *K*=2 to divide Θ into two sets: Θ_{major} and Θ_{minor}, according to L_{θ_k}. The subset Θ_{major} contains orientation elements that have large L_{θ_k}, meaning that they either have a few long edge lines (kerb, solid road markings) or a large number of short edge lines (broken road markings). Conversely, Θ_{minor} contains orientation elements that have small L_{θ_k} which may be discarded. From the Θ_{major} subset, we can define a new set of edge lines by

$$E_{\Theta} = \{e_k \in E : \theta_k \in \Theta_{major}\} \quad \text{...(7)}$$

Fig. 5 depicts the resulting edge maps of Fig. 3(b) in 2D and 3D after orientation discrimination.

5.2 Length Discrimination

As noted in Fig. 5, apart from the long edge lines there are other edge lines that are being classified into Θ_{major}, which are short and isolated. To further eliminate these lines, the edge lines in E_{Θ} are linked according to their orientations and locations, in a way similar to the method described in [14-15]. The two conditions are set below:

$$|\theta_i - \theta_k| < \varepsilon_1 \text{ and } |e_i - e_k| < \varepsilon_2, \quad \text{...(8)}$$

where $e_i, e_k \in E_{\Theta}$ and θ_i, θ_k are their orientation respectively. Both ε_1 and ε_2 are predefined limits. If two edge lines satisfy the above conditions, they are connected as given by Eq. (9), and Fig. 6 depicts the connected edge map of Fig. 5.

$$\bar{e}_k = (\bar{p}_{k,h}, \bar{p}_{k,t}) \quad \text{...(9)}$$

where $\bar{p}_{k,h} = \max_y \{p_{k,h}, p_{i,h}\}$ and $\bar{p}_{k,t} = \min_y \{p_{k,t}, p_{i,t}\}$

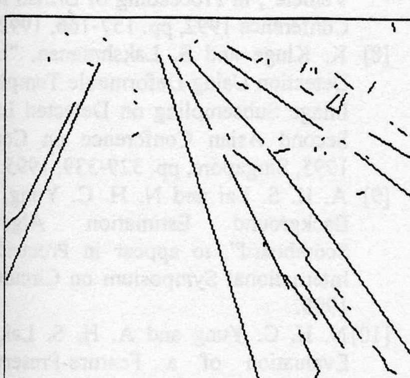


Fig. 6 – After line linking

As can be seen in Fig. 6, the edge map after line linking still contains a number of short and isolated lines. This problem can be dealt with by length discrimination. First, let us define the set of connected edge lines by:

$$L = \{|\bar{e}_k| \mid k = 0,\ldots,M-1\} \quad \text{...(10)}$$

Again, we apply *K*-means clustering with *K* = 2 to divide the edges segments into two sets: L_{long} and L_{short} simply according to $|\bar{e}_k|$. In this case, only L_{long} is retained, with L_{short} discarded. Therefore, the final set of edge lines can be described by Eq. (11) and the corresponding edge maps are depicted in Fig. 7.

$$L_e = \{\bar{e}_k : |\bar{e}_k| \in L_{long}\} \quad \text{...(11)}$$

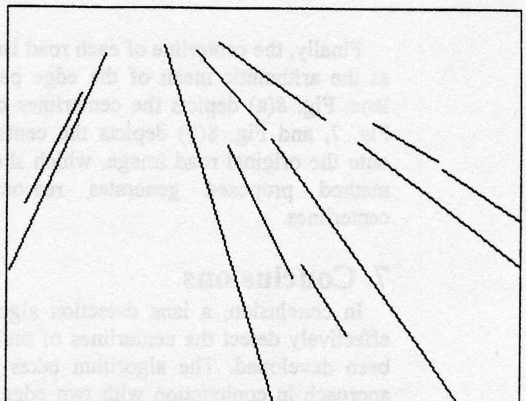


Fig. 7 – Edge map after length discrimination

6. Lane Analysis

Broadly, a road lane consists of two parallel edge lines with a perpendicular distance between them similar to the expected lane width. To determine which pair of lines defines a lane, let the perpendicular distance, d_{ik}, between a parallel edge line pair, $\{\bar{e}_i, \bar{e}_k\}$, be:

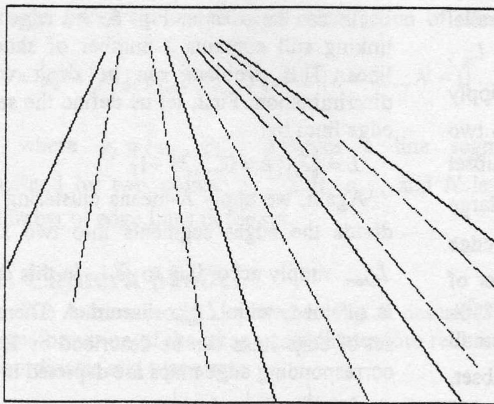
$$d_{ik} = \sqrt{(x_{p_{i,t}} - x_{p_{k,t}})^2 - (y_{p_{i,t}} - y_{p_{k,t}})^2}\,\sin(\theta_i - \alpha_{ik}) \quad \text{...(12)}$$

where $\alpha_{ik} = \tan^{-1}\left(\dfrac{y_{i,t} - y_{k,t}}{x_{i,t} - x_{k,t}}\right)$

If d_{ik} is similar to *W*, a predefined lane width, a single lane is detected. If d_{ik} is larger than *W*, possibly more than one lane is detected between the edge line pair, and the number of lanes, N_l can be estimated by:

$$N_l = \left\lfloor \frac{d_{ik}}{W} \right\rfloor \quad \text{...(13)}$$

To estimate the rest of the lanes, the other edge lines in L_e are tested with its adjacent lines until the whole set of lines is exhausted. Those edge lines that cannot form a pair are discarded at the end.



(a) Broken lines showing the centerlines

(b) Centerlines overlayed on the original image

Fig. 8 – Results of lane analysis

Finally, the centerline of each road lane is calculated as the arithmetic mean of the edge pair defining the lane. Fig. 8(a) depicts the centerlines calculated from Fig. 7, and Fig. 8(b) depicts the centerlines overlaid onto the original road image, which shows indeed the method proposed generates reasonably accurate centerlines.

7. Conclusions

In conclusion, a lane detection algorithm that can effectively detect the centerlines of multiple lanes has been developed. The algorithm takes an edge-based approach in conjunction with two edge discrimination heuristics which are the discrimination of edge orientation in 3D and edge length in 2D. A known camera model is used for the 2D-3D transformation on the edge orientation. In addition, as roads and lanes usually have parallel features, the 3D transformation helps to eliminate edges with other orientations efficiently. Also, the strong features of road and lanes assist in discriminating edges with short lengths. By using *K*-means clustering for the discriminations in both cases, no preset threshold is required. This improves the robustness of the algorithm. Experiment on real-world images acquired from one of the roads in Hong Kong proves that the algorithm is to be able to extract the required information with performance and errors at an acceptable level. As it is, the algorithm can potentially be applied to many visual surveillance problems.

8. References

[1] J Palen, "The need for surveillance in Intelligent Transportation Systems", Intellimotion, California PATH publications, vol.6, no.1, pp.1-10, 1997.

[2] L. T. Schaaser and B. T. Thomas, "Finding Road Lane Boundaries for Vision-guided Vehicle Navigation", in Vision-based Vehicle guidance, Springer-Verlag, New York, pp. 238-254, 1992.

[3] J. Weber, D. Koller, Q. T. Luong and J. Malik, "An Integrated Stereo-based Approach to Automatic Vehicle Guidance", in Proceeding of SPIE, vol. 2592, pp. 116-127, 1995.

[4] D. Frank, "Road Markings Recognition", in Proceeding of 1996 IEEE. International Conference on Image Processing, Lausanne, Switzerland, vol. II , pp. 669-672, 1996.

[5] C. Thorpe, M. H. Hebert, T. Kanada and S. A. Shafer, "Vision and Navigation for the Carnegie-Mellon Navlab", in IEEE Transactions on PAMI, vol. 10, no. 3, pp. 362-373, 1988.

[6] W. Kasprzak, H. Niemann and D. Wetzel, "Adaptive Road Parameter Estimation in Monocular Image Sequences", in Proceeding of British Machine Vision Conference 1994, pp. 691-700, 1994.

[7] N. W. Campbell and B. T. Thomas, "Lane Boundary Tracking for an Autonomous Road Vehicle", in Proceeding of British Machine Vision Conference 1992, pp. 157-166, 1992.

[8] K. Kluge and S. Lakshmanan, "Lane Boundary Detection Using Deformable Templates: Effects of Image Subsampling on Detected Lane Edges", in Second Asian Conference on Computer Vision 1995, Singapore, pp. 329-339, 1995.

[9] A. H. S. Lai and N. H. C. Yung, "An Effective Background Estimation Algorithm using Scoreboard", to appear in Proceeding of IEEE International Symposium on Circuits and Systems 1998.

[10] N. H. C. Yung and A. H. S. Lai, "Performance Evaluation of a Feature-Preserving Filtering Algorithm for Removing Additive Random Noise in Digital Images", in SPIE Journal - Optical Engineering, vol. 35, no. 7, pp. 1871-1887, 1996.

[11] A. H. S. Lai and N. H. C. Yung, "A New Feature Preserving Filter Algorithm Based on A Prior Knowledge of Pixel Types", in SPIE Journal – Optical Engineering, vol. 35, no. 12, pp. 3508-3521, 1996.

[12] J. A. Hartigan, "Clustering Algorithms", John Wiley & Sons, Canada, 1975.

[13] R. C. Gonzalez & R. E. Woods, "Digital image processing", Addison-Wesley Pub. Co., Ch.7, pp.416-428, 1992.

[14] G. W. Cook and E. J. Delp, "Multiresolution Sequential Edge Linking", in Proceedings of International Conference on Image Processing'95, vol. I, pp. 41-44, 1995.

[15] S. Vasudevan, R. L. Cannon and J. C. Bezdek, "Heuristics for Intermediate Level Road Finding Algorithms", in International Journal of Computer Vision, Graphics and Image Processing, vol. 44, pp. 175-190, 1998.