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The Robust and Fast Approach for Vision-based Shadowy Road Boundary Detection

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Abstract—**The objective of this paper is to develop a robust and fast algorithm for vision-based road boundary detection. This paper proposes a flexible scenario to integrate two algorithms developed by our previous work for improving the precision and robustness of the lane boundary detection, and applied on the vision-based automated guided vehicle (AGV) system. In our previous study on vision-based AGV, the road boundary detection was used to measure the attitude of vehicle in order to guide along the lane center and keeps correct attitude. The traditional edge detection methods were being substituted for the histogram-based color difference fuzzy cluster analysis (HCDFCM) to fast recognize the lane boundary. Although HCDFCM held faster and more precise features than traditional methods, the shadowy road interfered in the precision of lane boundary detection. In this paper, we use fuzzy inference system (FIS) to enhance the contrast of shadowy pixels, and find the similarity with the lane model to solve the fault of detection problem in the case of shadowy situation. For the sake of reducing computational times adaptively, the enhanced algorithm provides a scene for incorporating HCDFCM with shadow removing algorithm. If the lane center variation on the image plane is larger than a certain threshold initialized by HCDFCM, the adjustable scan region on image plane uses to reinforce the robustness of lane boundary detection. The proposed method developed a feasible way to detect the lane boundary with high quality and reduced computational times.**

I. INTRODUCTION

THERE are many study fields such as multifarious Advanced Highway System (AHS), Car Navigation System (CNS), Advanced Vehicle Control and Safety System (AVCSS) in Intelligent Transportation System (ITS). AVCSS provides the active safety and automatic driving device for vehicle. Through AVCSS the vehicle can be manipulated smoothly and actively avoid the occurrence of automobile accidents. One of the major topic of the AVCSS is the "road following" problem. Road following, enables a vehicle to navigate along a given portion of the road and most of the systems developed worldwide are based on lane detection by measure the relative position between the vehicle and the line of lane, and then keep the vehicle in appropriate position. Others [1-3] are not based on the preliminary detection of the road position, but derived the commands directly [4] for the actuators (steering wheel angles) from visual patterns detected in the incoming images. In this paper, the vision-based road boundary detection algorithm is developed for road following problems. We face two issues for the detection of road boundaries: 1) the presence of shadows, producing artifacts onto the road surface, and altering its texture, 2) the presence of other vehicles on the lane and partially occluding the visibility of the road. Although some systems have been designed to work on unstructured roads (without painted lane markings) [2] or on unstructured terrain [5-6], generally lane detection relies on the presence of painted road markings on the road surface [7-15]. Therefore, lane detection generally based on the localization of a lane marking in the acquired image, it performed analysis of a single image. And in our previous study on vision-based AGV, the AGV must extract the road boundary fast [16].

Most of the analytic methods were used a simple model to characterize the roadside as a straight and rectilinear in the image [17-20]. It might generate errors on the vehicle localization if the road is not straight or flat. Besides, other technique likes LOIS system [21] used a deformable template approach in order to handle situations such as the lane edges in image have relatively weak local contrast and/or there are strong distracting edges dues to shadows, puddles, pavement cracks, etc. The RALPH system [22-24] extracted a trapezoidal region of the forward looking road image by considering the vehicle's velocity, current visibility and perspective effect obtained by straightening transform of the image intensity. After being resampled , the extracted region transforms into a plan-view road. The straightening transform applies to this plan-view road image and the lanes are found from the intensity information of the transformed result. However, the crux of RALPH is matching technique that adaptively adjusts and aligns a template to the averaged scan line intensity profile in order to determine the lane's curvature and lateral offsets.

The purpose of this paper is to design a robust algorithm to detect the lane boundary with high quality and reduced computational times adaptively. According to the histogram-based color difference fuzzy cluster analysis (HCDFCM) algorithm [25] used only one scan line to find the lane boundary, thus can save the computing time and the amount of processing data. However, the HCDFCM based on the color difference features of the road edge to determine the lane boundaries, thus the shadowy portion destroyed the features and the failed detection may be appeared.

According to road shadow removing algorithm [26] developed in our previous works can solve the HCDFCM problem in the case of shadowy road. For the sake of reducing

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computational times adaptively, we propose a flexible scenario that combines HCDFCM with shadow removing algorithm. We will use shadow removing method to detect the lane boundary if the variation of the lane's center on the image plane is larger than a certain threshold by HCDFCM. We will adjust the scan region according to the variation of lane's center while using shadow removing method.

The paper organized as follows: Section II presents the road detection algorithm (HCDFCM) and the situation with shadow. Section III presents the proposed methods and results. Section IV is conclusions.

II. ROAD DETECTION PRINCIPLES

The phenomenon that color difference between an object boundary and background was the basis of HCDFCM algorithm. The color difference feature of an object edge can be used to detect lane boundaries as follow steps:

A. *Data preprocessing phase*

1. Get color pixels set from one horizontal scan line of the road image.
2. Calculate the Euclidean distance *R(k)* between two consecutive pixels (the k_{th} pixel and the $k+1_{th}$ pixel).
3. Calculate the histogram function *H(R)* and illustrated as Fig. 1, which is the amount of the *R* (Euclidean distance between two consecutive pixels).

B. *Fuzzy clustering analysis phase*

To divide *H(R)* into two clusters following (1) and (2), one is the group of small color difference, and the other one is the large color difference group. The initial cluster numbers is two, the centre of the clusters is expressed as $\mathbf{V} = \{V_i | i = 1,2\}$, give the two initial cluster center are V_1=0 and V_2 =*max(R)*.

$$V_i = \frac{\sum_{R=0}^{\max(R)} (U_{iR})^m H(R) R}{\sum_{R=0}^{\max(R)} (U_{iR})^m H(R)} \tag{1}$$

$$U_{iR} = \frac{1}{\sum_{j=1}^{c} (\frac{d_{iR}}{d_{jR}})^{\frac{2}{m-1}}}, \text{ where } d_{iR} = |V_i - R| \tag{2}$$

C. *Outcome phase*

The step B executes iteratively until V_i not change or converge to certain range of error in (1). The cluster centers are V_1 and V_2 which represented as the vertical location of the scan line. The portion of *R(k)* that is greater than V_2 will be regarded as the border location of the scan line in the image, and the inner pair of *R(k)* is the detected lane boundary. In Fig. 2(a), both of the *R*(65), *R*(240) and *R*(320) are all greater than V2, so that the lane boundary detected at the pixel 65 and pixel 240. The actual detected lane boundary is marked by a black line in the image plane shown as Fig. 2(b).

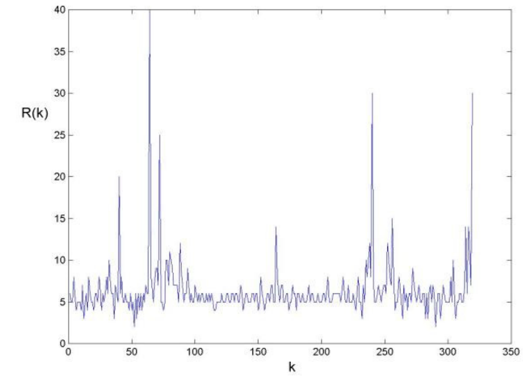
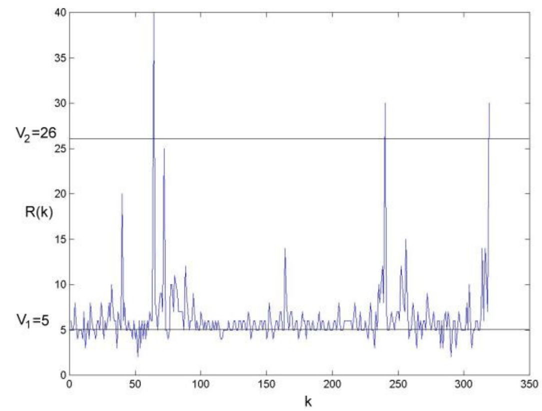
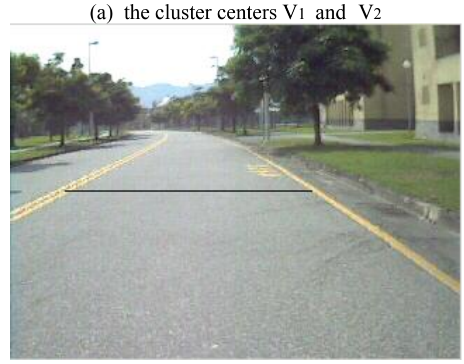


Fig. 1. Histogram function *H(R)*



(a) the cluster centers V1 and V2



(b) the boundary of the scan line

Fig. 2. The outcome example of HCDFCM algorithm

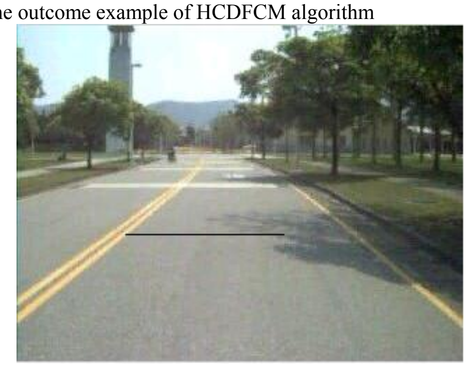


Fig. 3. The shadowy road boundary can not detected by HCDFCM

Although HCDFCM algorithm could find the edge of lane quickly, and not influenced by the intensity of the sun illumination. But in the case of shadowy road, the shadowed portion cover one side of the real boundaries, will shorten the width between two sides of boundary. So that, illustrated as Fig. 3, HCDFCM could not find the cluster centers correctly and the correct position of the lane boundary. Therefore, the robustness of HCDFCM is the key factor to obtain a reliable and precise control for the vision-based AGV.

III. The Proposed Method

According to the results of Section II, the shadowed portion destroys the pixels value of the road image. We have developed the shadow removing algorithm in our previous works for solving the incorrect detection in case of shadowy road. For the purpose of reducing computational times adaptively, we combine HCDFCM with shadow removing algorithm in this paper. We propose a flexible scenario to integrate two algorithms for improving the precision and robustness of the lane boundary detection, and applied on the vision-based AGV system. If the lane center variation on the image plane is larger than a certain threshold initialized by HCDFCM, the adjustable scan region on image plane will be used to reinforce the robustness of lane boundary detection.

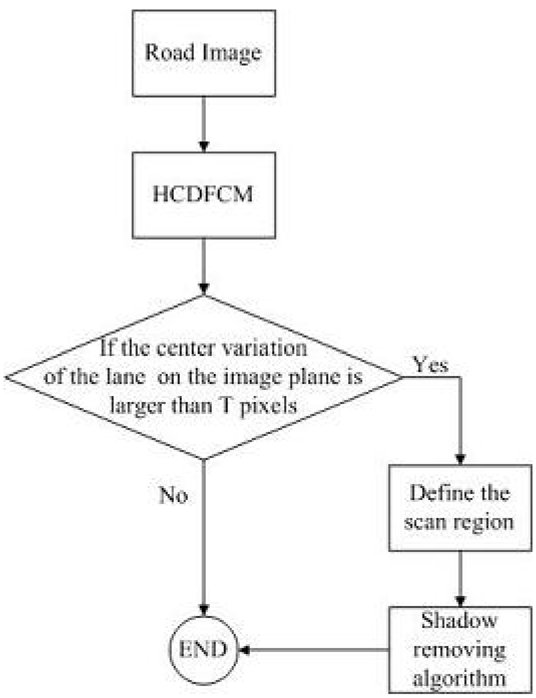


Fig. 4. the proposed algorithm flowchart

The adaptive method for improving the lane boundary detection is divided two major parts:

A. Define the scan region

The scan region is marked from V_1 to V_m in the image shown as Fig. 5(a). The scan region should be adjusted proportional to the center variation of the lane as Fig. 5(b).

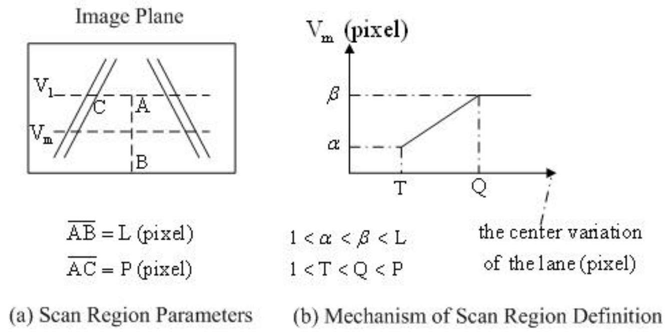


Fig. 5. The mechanism of the scan region definition and parameters

B. Shadow removing algorithm

The shadow removing algorithm is based upon two stages: 1) Using Fuzzy Inference System (FIS) to enhance the contrast between the shadowed and unshadowed pixels value. 2) To compare the preprocessed shadowy image with the road models which are not affected by shadow in order to find out the most similar pair. For the first stage, the main problem is the difficulty to establish the range of pixels that the shadowed image needs to enhance. In this paper, we defined a set of fuzzy decision rules as the criteria to contrast sharply with shadowed image. For the second stage, the purpose is to reconstruct the shape of shadow destroyed roadside. We developed a method to reconstruct the line marking by means of roadside models that are not broken by shadow, and compare with shadowed image to estimate the similarity values. And then, the superior value of similarity is selected to reconstruct the shadowy line marking.

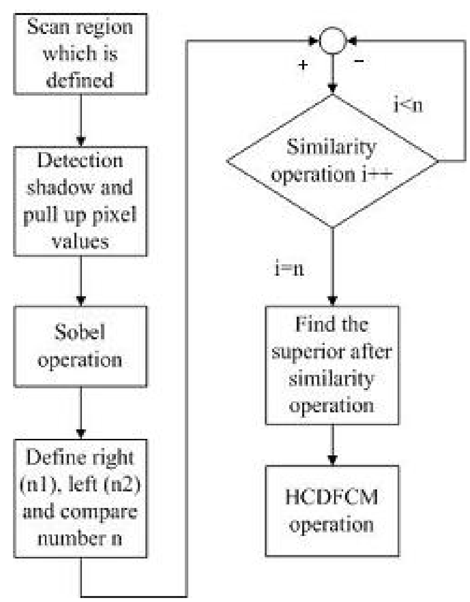


Fig. 6. the shadow removing algorithm flowchart

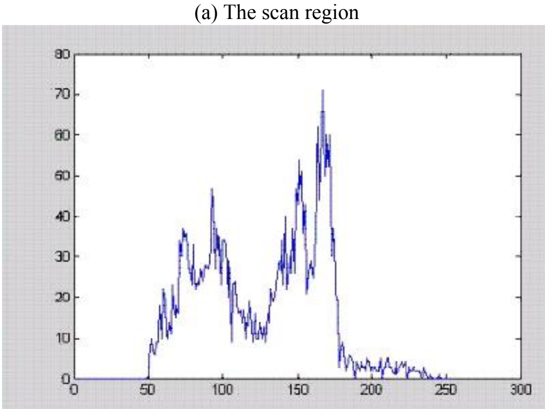
The flowchart of the shadow removing algorithm illustrated as Fig. 6. The detail steps are as follows:

Step 1. The scan region definition:

Since single scan line in HCDFCM has not enough information for recognizing the shadowy road. So that, the adaptive scan region applied following Fig. 5(b). Example for

Fig. 3, the appropriate scan region calculated as Fig. 7(a) and the histogram of scan region shown in Fig. 7(b). The scan region's pixel values distributed in the range between 40 and 50, and the asphalt image is around between 150 and 180. According to those statistics data, the destroyed pixels can be improved by fuzzy inference system in next step.

(a) The scan region



(b) Histogram

Fig. 7. scan region and histogram

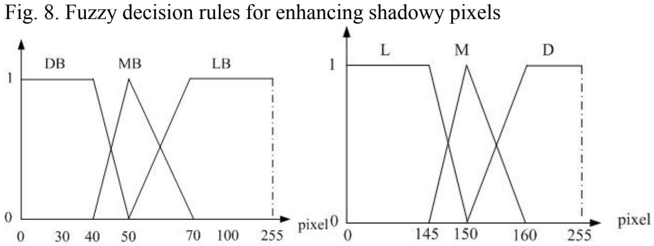
Step 2. Detection shadow:

The purpose of this step is to enhance the contrast between shadow and asphalt road by seven fuzzy decision rules illustrated as Fig. 8. The input and output linguistic variables are defined as Fig. 9(a) and (b), respectively.

R^1 If Input is LB then output is M
R^2 If Input is LB then output is D
R^3 If Input is MB then output is L
R^4 If Input is MB then output is M
R^5 If Input is MB then output is D
R^6 If Input is DB then output is L
R^7 If Input is DB then output is M

LB light black   L light
MB medium black   M medium
DB deep black   D deep

Fig. 8. Fuzzy decision rules for enhancing shadowy pixels



(a) Input Fuzzy sets (b) Output Fuzzy sets

Fig. 9. Linguistic variables of fuzzy decision rules

The processing result is shown in Fig. 10. We can clearly to see the compartment between the shadow and line marking. More useful, the result can help us to recognize and reconstruct the road model.

Fig. 10. FIS result for enhancing the shadowy pixels

Step 3. Sobel operation:

Sobel operation is a popular image processing method for edge detection. The Sobel mask operators are looking for the edge in both horizontal and vertical direction and then combine them. In this paper, Sobel operation is used to detect edge after previous steps for contrasting the shadowy pixels. Fig. 11 shows the result after Sobel operation, because the shadowy pixels have contrasted, therefore the edge detected easily. The result of this step provides the necessary information for the road model to compare and find the similarity to reconstruct the roadside.

Fig. 11. The result of Sobel Operation

Step 4. Definition width and compare number:

This step is based on the result after enhance the contrast between lane-marking and asphalt road. Using Sobel operator to detect the edge and can clearly to know how to figure out the edge from Fig. 11. However, the processed image after Sobel operation still contain some noise and maybe affect the recognition result. Therefore, we must eliminate noisy portion to make sure the real lane-marking position, and then use HCDFCM to confirm the left and right road boundary. In this step, we use road model that does not affected by shadow and compare with the image which after Sobel operation in previous step. Before performing, we must set the parameters about the road right and left model shown as Fig. 12 according to the front-view image. The right model width $n2$ is equal to 10 and the left model width $n1$ is 25. The choice of these parameters based on the front-view image, therefore it may be refined progressively with the images and self-adapts to any road type. The parameter n is the total amount that needed to compare with the Sobel image. In this paper, the parameter n=4, it means that the left and right roadside are needed to compare four times.

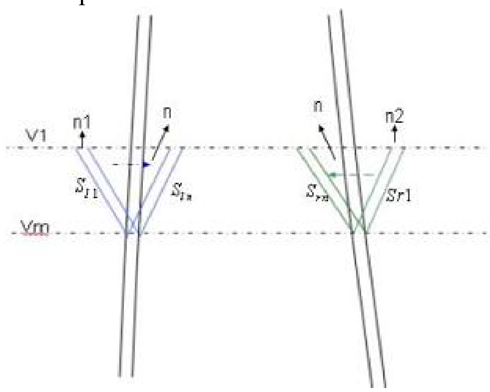


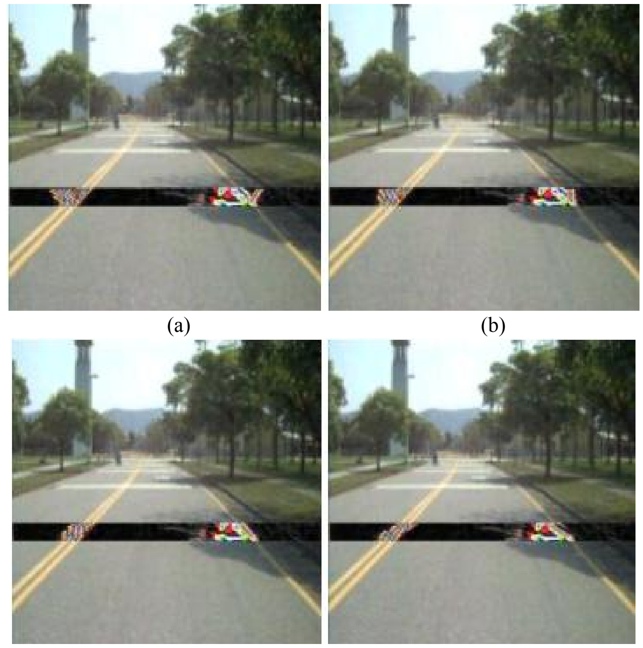
Fig. 12. Similarity Chart

Step 5. Similarity degree operation:

The objective of this step is to detect the road features, and compute the similarity degree between the road model and the Sobel image. Fig. 12 shows the similarity chart. There are four different directions for the left and right roadside models to compare with the image. That means the road model also can compare with the shadowy noise image, but the noise does not affect the precision to reconstruct the real road model. The similarity degree of left roadside S_{li} and right roadside S_{ri} are represented as (3) and (4), where M_{xy} and N_{xy} denotes the road model pixel value and the Sobel image pixel value, respectively. If $N_{xy} > M_{xy}$, then the similarity degree equation is above (3) and (4), else if $M_{xy} > N_{xy}$ then the similarity degree equation is lower than (3) and (4). The equations calculate every pixel's similarity degree in the range from 0 to 1. According to the comparison number $n = 4$, we could obtain four similarity degree result for the left or right roadside. The similarity factors used to define the likeness relative function with respect to find the optimal number of line detection to the road images. Fig. 13 presents all of the four different search procedures.

$$S_{li} = \left\{ \begin{array}{l} \sum_{x=1}^{n1} \sum_{y=1}^{m} M_{xy}/N_{xy} \quad (if N_{xy} > M_{xy}) \\ \sum_{x=1}^{n1} \sum_{y=1}^{m} N_{xy}/M_{xy} \quad (if M_{xy} > N_{xy}) \end{array} \right\} (i = 1..n,\ x = 1..n1,\ y = 1..m) \tag{3}$$

$$S_{ri} = \left\{ \begin{array}{l} \sum_{x=1}^{n2} \sum_{y=1}^{m} M_{xy}/N_{xy} \quad (if N_{xy} > M_{xy}) \\ \sum_{x=1}^{n2} \sum_{y=1}^{m} N_{xy}/M_{xy} \quad (if M_{xy} > N_{xy}) \end{array} \right\} (i = 1..n,\ x = 1..n2,\ y = 1..m) \tag{4}$$



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

Fig. 13. Similarity degree search procedure

Step 6 Choose Superior:

The goal is to choose the optimal similarity degree number and reconstruct the road model. Based on (3) and (4), the purposed selection method (5) is to determine which direction has the maximum similarity degree. Fig. 14 shows the reconstruction profile of the road shape result with using HCDFCM algorithm. Thus, we can figure out the affect by the shadow and use HCDFCM to detect the road boundary.

$$\begin{array}{l} \max_{l} = \max(S_{li}) \\ \max_{r} = \max(S_{ri}) \end{array} \tag{5}$$

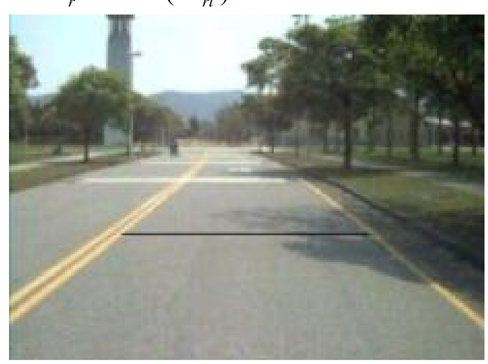


Fig. 14. Reconstruct image

For the continuous images, the recognition results are shown as Fig. 15. From the shadow removing algorithm described above, the purpose is to improve the precision and robustness of recognition result. Here, the processing result provides information about road marking for the lane detecting system to estimate the lane shape parameters. When these parameters are decided, we can use the reconstruction information to find the left and right boundaries.

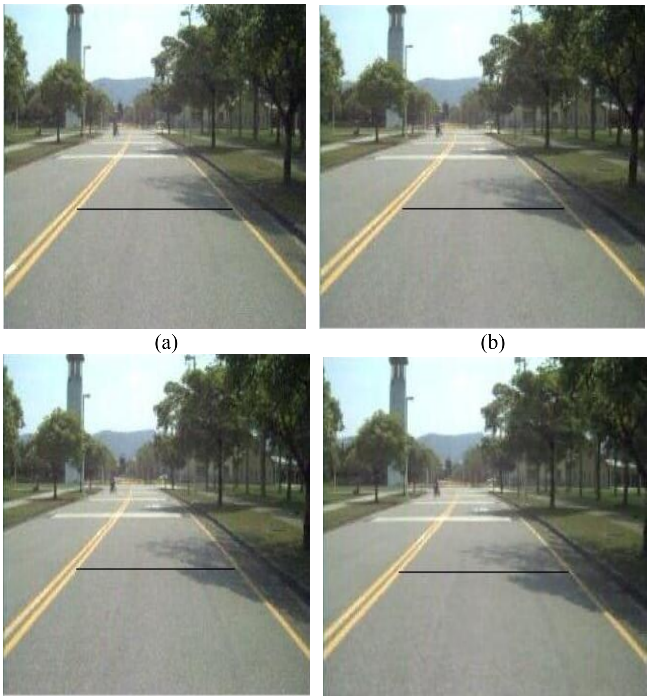

(a) (b) (c) (d)

Fig. 15. The recognition results of continuous images

IV. CONCLUSIONS

In this paper, we use fuzzy inference system to enhance the contrast of shadowy pixels, and find the similarity with the lane model to solve the fault of detection problem in case of shadowy situation. For the sake of reducing computational times adaptively, the enhanced algorithm provides a flexible scenario for incorporating HCDFCM with shadow removing algorithm. If the lane center variation on the image plane is larger than a certain threshold initialized by HCDFCM, the appropriate scan region on image plane derived to reinforce the robustness of lane boundary detection. The proposed method developed a feasible way to detect the lane boundary with high quality and reduced computational times.

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