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A Robust Vision-based Lane Boundaries Detection Approach for Intelligent Vehicles

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Abstract: The intelligence of the vehicle is identified by the surrounding environment. Lane detection is one of the vision-based features that used for assisting and controlling tasks for the intelligent vehicles. In this study, an overview of lane detection approaches is presented and then a model, based on inverse perspective mapping, edge detection and fitting lines algorithm is introduced. The system was tested on the urban road image data base in different light conditions. The performance of the system in term of lane marking detection was 97.2%. The results were accurate and robust with respect to the shadows and worn lane markings and also appropriate for real time procedure.

Key words: Intelligent vehicles, inverse perspective mapping, edge detection, Hough transform, lane boundaries

INTRODUCTION

All around the world there are great efforts to develop Intelligent Transportation Systems (ITS) (Ishak *et al*., 2006; Hannan *et al*., 2010a, b; Chu *et al*., 2011; Ayati *et al*., 2011; Huo *et al*., 2011). The aim of these researches was to enhance an assistant driving system to help the driver to make better decisions on the road or even to replace the driver to achieve autonomous vehicles (Hannan *et al*., 2008a; Idris *et al*., 2009; Xiong and Shiru, 2010; Ori *et al*., 2011a, b). These systems can increase the driving safety and make it more comfortable (Hannan *et al*., 2006, 2008b; Broggi *et al*., 2010; Ohakwe *et al*., 2011; Hannan *et al*., 2011a, b).

Visual sensors play a great role in automatic driving system (Hu *et al*., 2004; Yanqing *et al*., 2010; Zhang and Xie, 2011). A lot of methods based on visual sensors are introduced to accomplish some assistant driving tasks such as lateral control, lane departure warning, road sign detection, obstacle detection, etc. (LeBlanc *et al*., 1996; Bertozzi *et al*., 2000; Arlicot *et al*., 2009). The challenging problem to realize some of these goals is to detect the lane boundaries of the road (Gonzalez and Ozguner, 2000; McCall and Trivedi, 2004; Zhang and Zhan-ming, 2011). Many researches has been developed in this area, however, the complicated nature of this problem due to shadows, vehicles covering the lines, worn marks, etc., it is not completely solved (Bertozzi *et al*., 2002).

Several road models have been proposed for lane detection and tracking. These methods employ mathematical models to fit lane boundaries (Bertozzi and Broggi, 1998; Hofmann *et al*., 2001; Yu *et al*., 2005; Dickmanns, 2007). The accuracy of these models is depended on their complexity. Simpler models do not fit the lane boundaries accurately though they are more robust to noise than complex models. Some other methods have been developed based on AI and machine learning techniques, such as neural networks, SVM, etc. (Hu *et al*., 2004; Sha *et al*., 2007). These systems need to be trained to distinguish between road and non-road regions. Color processing technique is also used to detect the lane boundaries by using scene understanding (Rasmussen, 2002; He *et al*., 2004). This technique applies likelihood measures based on the initial determined image of the road to find further edges of that (Wang *et al*., 2004; Boumediene *et al*., 2007; Arlicot *et al*., 2009).

In this study, vision-based lane boundaries detection approaches related to this problem, have been reviewed and a comparison between them has been made to state the existing problems for future works. Then it has introduced a robust model to detect the lane boundaries based on inverse perspective mapping technique, edge detection and Hough transform to fit the lines for lane markings.

OVERVIEW OF THE SYSTEMS

One of the earliest works in the area of lane detection is done by using LOIS (Likelihood of Image Shape) lane detection algorithm which is consisted of three components (Kluge and Lakshmanan, 1995). In the first part the shape model is described the lane edges with

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some parameters. In the second one the likelihood function is used to find out how well the given set of shape parameters matches the data of the image and finally in the third part the optimization algorithm (Metropolis algorithm) is employed to determine the best set of lane shape parameters for the given image. This method was a great contribution although the accuracy is not good enough. Another system has designed to remove the perspective distortion effect to simplify the image (Takahashi *et al*., 2003). In the next step, the edge candidates for the lane markings are extracted by using horizontal differentiation. After that, the straight lines will be determined by using the Hough transform. By analyzing the lane marking parameters of candidates, those which fit the best will be selected. Lopez *et al*. (2007) introduced a method that detects lane markings as ridges instead of edges and then the RANSAC algorithm is used to fit a parametric model of lane boundaries.

A number of techniques have been studied in order to use artificial intelligence for this purpose. An approach based on decision tree is one of them (Gonzalez and Ozguner, 2000); first, a histogram based segmentation used to extract objects from the image such as road, obstacles or lane markings candidates. In order to discard non lane marking objects, some featured related to the geometry, shape and position of the objects has been used. They used the decision tree to classify the lane markings candidates with different confidence levels. The last step is to group all objects that may be lane markings due to confidence levels. This system is still sensitive about noise and needs a good pavement for roads to work properly. Another method based on ant colony optimization to solve difficult combination problems for finding lane markings (Bertozzi *et al*., 2002). In this method a number of independent agents are used to explore and track lines in the image for detecting the lane. However, the results of lane markings extractions are not smooth.

A comparative study on the performances of classifiers for lane detection concluded that all classifiers perform better than intensity bump method (Kim, 2008). In his proposed system, for further reduction of the computation time, a cascade classification is applied; fist using a low threshold intensity bump classifier and then the ANN classifier. Then the lane marking detection algorithm based on RANSAC combined with a particle filter is introduced. Shadows and complicated lane markings reduce dramatically the performance of this approach.

Some algorithms are presented which using multiple features for obtaining the lane boundaries. A lane tracking system proposed based on distillation algorithm, multiple cues and particle filtering (Apostoloff and Zelinsky, 2003). In this method several cues are combined for lane tracking such as road edge cue, road color cue, etc. This approach is robust for complicated conditions of shadows or poor marking although it cannot track the curves of the roads. Another system used Three-Feature Based Automatic Lane Detection Algorithm (TFALDA) to detect the lane (Yim and Oh, 2003). This system calculates similarity among all candidates in a three dimensional space spanned by the three features of lane markings (starting position, direction (or orientation) and gray-level intensity). The algorithm is consisted from three components (preprocessing, automatic lane detector and lane inference system) to find the best candidate out of all possible ones. He *et al*. (2004) presented a method to determine the road parameters. This system estimates three boundaries candidates based on edge detection and their curvatures model. The results are combined with the color information of the captured image to calculate the road parameters.

Steerable filters are also employed to extract lane markings within the image (McCall and Trivedi, 2004). The information about the state of vehicle such as speed and steering angle is fed to the system to calculate the state of vehicle and the road. By using a Kalman filter, the state of vehicle and road will be updated. This method is robust with respect to the shadows and different lighting conditions. However, it has shortcomings for detecting curved roads because it relies on a linear model. A method based on color differences of pixels of the road is also presented for extracting the lines (Huang and Pen, 2009). They employed Sobel mask for detecting the edges. Then they obtained two main groups of points with same slopes from two points at bottoms of right and left of the image, respectively. Finally, they draw the road lines by applying the first order least square approximation.

Mastorakis and Davies (2011) introduced an improved line detector algorithm based on RANSAC algorithm. The algorithm operates in a loop to check for all existent lines in the image. Two variables, d_f (fit distance which is used to find each line in turn) and d_d (delete distance which is used to delete data points on and near to each line after it is detected) are hired after locating the potential midpoints in the image.

Most of lane detection systems are used to avoid unintended lane departures. These systems anticipate the time of lane departure by comparing the predicted vehicle's path with the calculated road geometry ahead of vehicle (LeBlanc *et al*., 1996). Several parameters are considered to distinguish between intended and unintended departures according to the driver behavior, such as announcing by blinkers, braking and high steering and cutting a curve activity (Risack *et al*., 2000).

A system based on Edge Distribution Function (EDF) is also presented to detect the lane departure of the vehicle (Lee, 2002). However, this method avoids working on a noisy road surface by identifying such conditions in advance. This algorithm does not perform well on sharp curved roads. Lee *et al.* (2003) enhanced this technique by estimating the position and the orientation of lane boundaries at the same time.

This study has suggested an accurate system which in our effort was concerned on selecting an appropriate region of interest for processing, removing noise from data, extracting features, generating candidates for lane markings and finally finding the lane boundaries precisely.

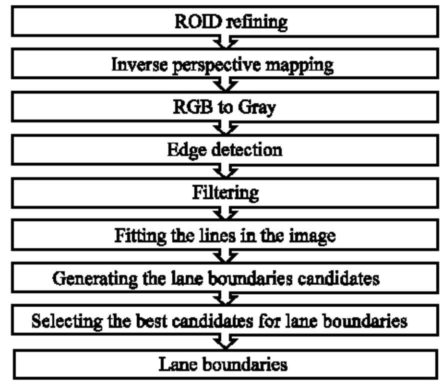


Fig. 1: The presented lane detection process

METHODS AND SYSTEMS

The purpose of lane detection is to report the position of the lane boundaries with respect to the vehicle (McCall and Trivedi, 2004). According to the review of the lane detection approaches there are several important issues to deal with such as detecting roads with worn lane markings, detecting the curves, processing in real time, detecting with shadows, etc. (Mastorakis and Davies, 2011). In this paper we have proposed a method (Fig. 1) which would be able to determine lane boundaries accurate and also to be robust to the shadows.

We divided our approach in three sections as follows:

- Inverse perspective mapping
- Edge detection and filtering
- Fitting lines algorithm

Inverse perspective mapping: In the pre-processing section by using number of techniques we have tried to make the image simpler for further analyzing. The first step was to eliminate the perspective effect to get the bird's eye view of the road. In this procedure, according to the real world space, the incoming image was remapped to a new two-dimensional image (Bertozzi and Broggi, 1998; Broggi *et al*., 2010).

The real world and incoming image spaces are as follows:

- $R = \{(x, y, z)\}|E^3$ which represents the 3-D real world space coordinates
- $I = \{(u, v)\}|E^2$ which represents the 2-D incoming image coordinates

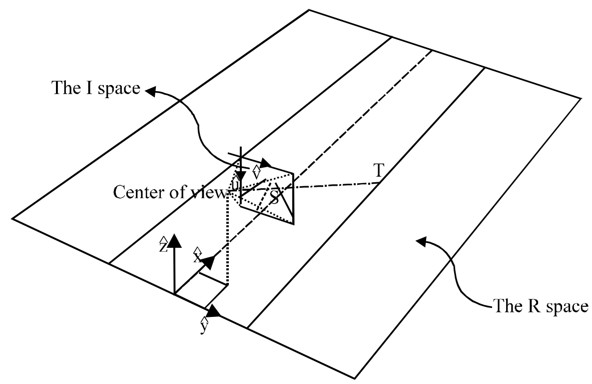


Fig. 2: The relation between the real world and the captured image

The assumption for the real world was that the road is flat so z = 0. The relationship of two spaces is shown in Fig. 2.

2-D image from the 3-D real world these parameters should be known (Fig. 3):

- Center of view: The position of camera $E = (i, j, k)|R$
- Direction of view: The optical axis $\hat{e}$ is defined by these angles
- $\bar{\Lambda}$: The angle between the projection of the optical axis $\hat{e}$ on the plane z = 0 and the x axis
- $\bar{\Phi}$: The angel between the optical axis $\hat{e}$ and versor g
- Angular aperture of camera: That is 2λ
- Resolution: Camera resolution is $m \times m$

The final mapping function for f: I|R with respect to u and v is given by Eq. 1:

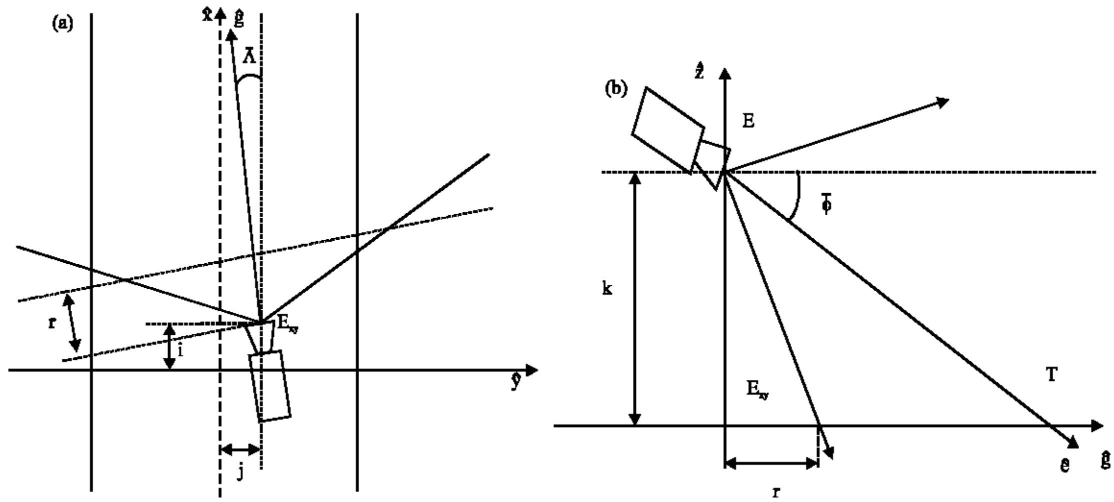


Fig. 3(a-b): (a) The x-y plane in the R space and (b) The z-g plane

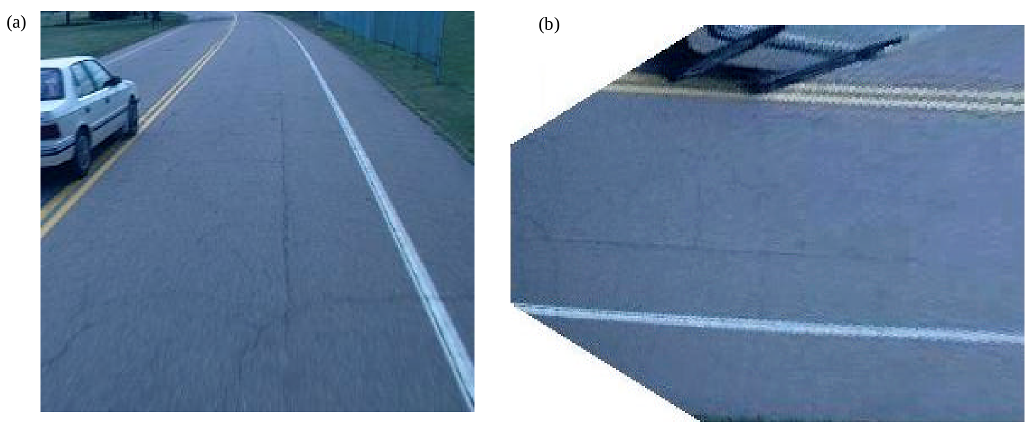


Fig. 4(a-b): (a) The original image and (b) The bird's eye view of the image

$$
\begin{aligned}
x(u,v) &= k\times\cot\left[(\bar{\Phi}-\lambda)+u\frac{2\lambda}{m-1}\right] \\
&\times\cos\left[(\bar{\Lambda}-\lambda)+v\frac{2\lambda}{m-1}\right]+i \\
y(u,v) &= k\times\cot\left[(\bar{\Phi}-\lambda)+u\frac{2\lambda}{m-1}\right] \\
&\times\sin\left[(\bar{\Lambda}-\lambda)+v\frac{2\lambda}{m-1}\right]+j \\
z &= 0
\end{aligned}
\tag{1}
$$

With u, v = 0, 1,..., m-1. Therefore, a point like S with coordinates (u, v) in the I space, would be returned by point T with coordinates (x, y, 0) in the R space as it is shown in Fig. 2.

R|I mapping: This dual mapping H: R|I is defined as follows:

$$
\left|
\begin{aligned}
u(x,y,0) - \frac{\operatorname{arctg}\left[\frac{k\sin\Lambda(x,y,0)}{y-j}\right]-(\bar{\Phi}-\lambda)}{\frac{2\lambda}{m-1}} \\
v(x,y,0) - \frac{\operatorname{arctg}\left[\frac{y-j}{x-i}-(\Lambda-\lambda)\right.}{\frac{2\lambda}{m-1}}
\end{aligned}
\right.
\tag{2}
$$

The perspective effect was removed by remapping the incoming image by using these two last equations (Fig. 4).

Edge detection and filtering: Edges have some of the most valuable information in an image. They are useful for measuring the size and the shape of objects and also finding patterns in image processing. There are several edge-detecting algorithms but the basic rule is to find local discontinuity in pixels that exceeds the particular threshold (McAndrew, 2004).

Many of edge detecting methods are based on differentiation. If we assume the function of image is f(x) then the differentiation is given by:

$$\frac{df}{dx} = \lim_{l \to 0} \frac{f(x+l) - f(x)}{l} \quad (3)$$

Since, the image is discreet the smallest value for h is 1 so we have a discreet derivative which is defined by:

$$f(x+1)\text{-}f(x) \quad (4)$$

For two dimension images, by using partial derivatives, the gradient vector is as follows:

$$\left[\frac{\partial f}{\partial x}\ \frac{\partial f}{\partial y}\right] \quad (5)$$

The expression f(x+1)-f(x) will produce the vertical and horizontal filters for detecting edges in the image. In our method Sobel edge detection was used to find horizontal and vertical derivatives (S_x, S_y) of the image (I) by convolving the Sobel filters with the original image as it shown below:

$$S_x = \begin{bmatrix} -1 & 0 & +1 \\ -2 & 0 & +2 \\ -1 & 0 & +1 \end{bmatrix} * I$$
$$S_y = \begin{bmatrix} -1 & -2 & -1 \\ 0 & 0 & 0 \\ +1 & +2 & +1 \end{bmatrix} * I \quad (6)$$

For each pixel the gradient magnitude and the gradient's direction would be defined by Eq. 7:

$$S = \sqrt{S_x^2 + S_y^2}$$
$$\Upsilon = \mathrm{arcg}\left(\frac{S_y}{S_y}\right) \quad (7)$$

At this level in order to reduce the noise in the image, a non-linear spatial filter named median filter was used. In general an idea of median filter is replacing a noisy value with the middle value of its neighborhood pixels, while the edges are preserved (McAndrew, 2004). Therefore, the image became smoother and line detection would be easier in the next part (Fig. 5).

Fitting lines algorithm: In this part to extract the lane boundaries we used the Hough transform that is defined

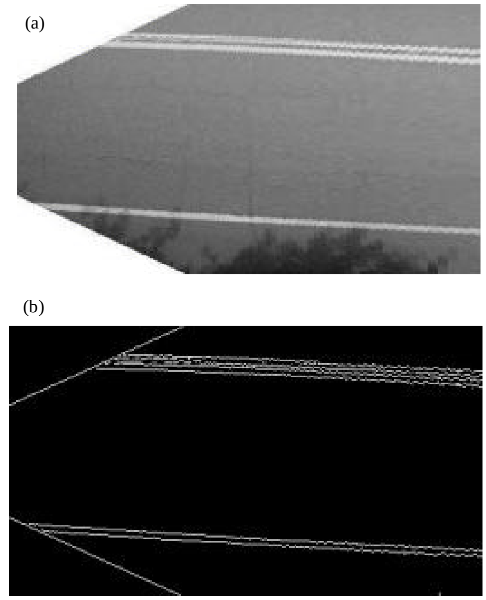


Fig. 5(a-b): (a) The remapped image in gray and (b) The remapped image after edge detection

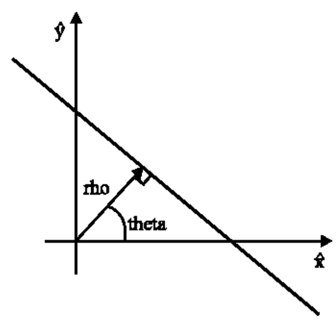


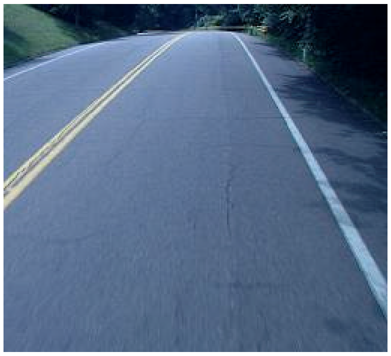
Fig. 6: Variables rho and theta generated by Hough transform

to detect lines in images (McAndrew, 2004). The parametric concept of line that is used in this function is this:

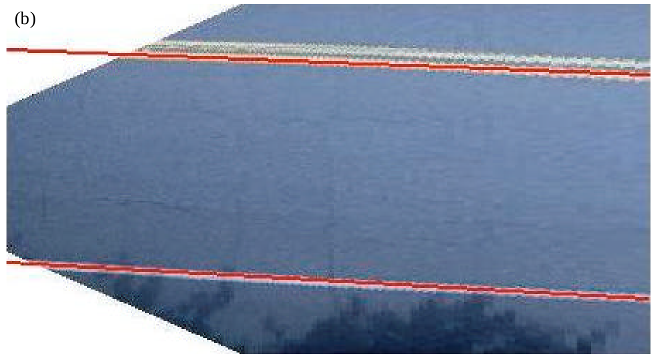
$$\text{rho} = x \cos(\text{theta}) + y \sin(\text{theta}) \quad (8)$$

The rho is the perpendicular distance from the origin to the line. The theta is the angle between the perpendicular vector and the x-axis (Fig. 6). The Hough transform generates for every pixel a rho and theta. A line would be extracted from those pixels that have the same amount for rho and theta. For ignoring unexpected lines in an image, we needed just those lines which are compatible with the nature of lane boundaries.

(a)



(b)



(c)

Fig. 7(a-c): (a) The original image, (b) Lane markings detected on the remapped image and (c) Lane markings on the image

The peaks of variables rho and theta that have been generated by the Hough transform were located in a particular matrix. The lane boundaries were extracted by using the matrix of the peaks and variables rho and theta. In order to detect the markings more precisely several characteristics of the road has been considered, such as the length of the line, the distance between two lane boundaries, the level of brightness of the lane markings, etc.

The result was the position of lane boundaries on the image with respect to the vehicle (Fig. 7). By analyzing this data some tasks such as lane departure warning, keeping lane assistance, etc., would be possible (Gonzalez and Ozguner, 2000).

RESULTS AND DISCUSSION

Experimental results were achieved by using the VASC Image Database VASC (2011). The dimension of images used was 256×240. The results for lane detection were obtained by programming in MATLAB program.

This approach was used to detect the lane boundaries regarding vehicle's position. The method was tested on road images with shadows and different pavement and curvature. In Fig. 8, there are some results of detected lane boundaries from the bird's eye view which would be used for further control actions such as lateral control.

Table 1: Performance of the system

Road type	No. of images	Failed	Success rate (%)
Urban-cloudy	300	8	97.33
Urban-sunny	200	6	97.00
Total	500	14	97.20

The detected lane markings from the normal view were also showed in Fig. 9. The time needed for executing this algorithm for every frame was less than 0.36 sec. The accuracy for this method was 97.2% which is shown in Table 1. The method was tested in two conditions; images of urban road when it was sunny and also cloudy. In the sunny condition, there were images which had shadows on the road. Our system performed better in a cloudy condition because the contrast in the image was less than sunny condition although the success rate is still high in the sunny situation.

The proposed algorithm performed well in detecting lane boundaries and the success rate shows that the system reliability is high. However, because of the

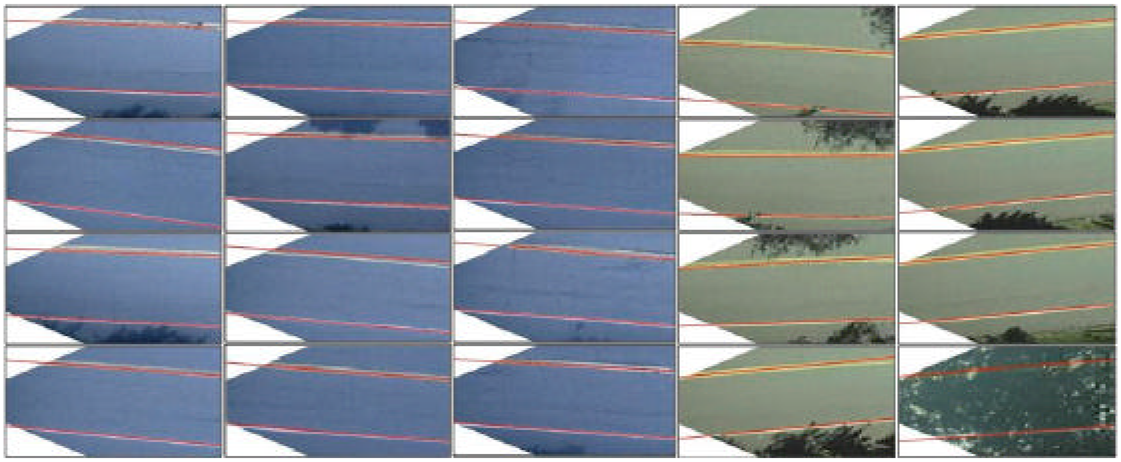


Fig. 8: Lane boundaries detected in the bird's eye view images

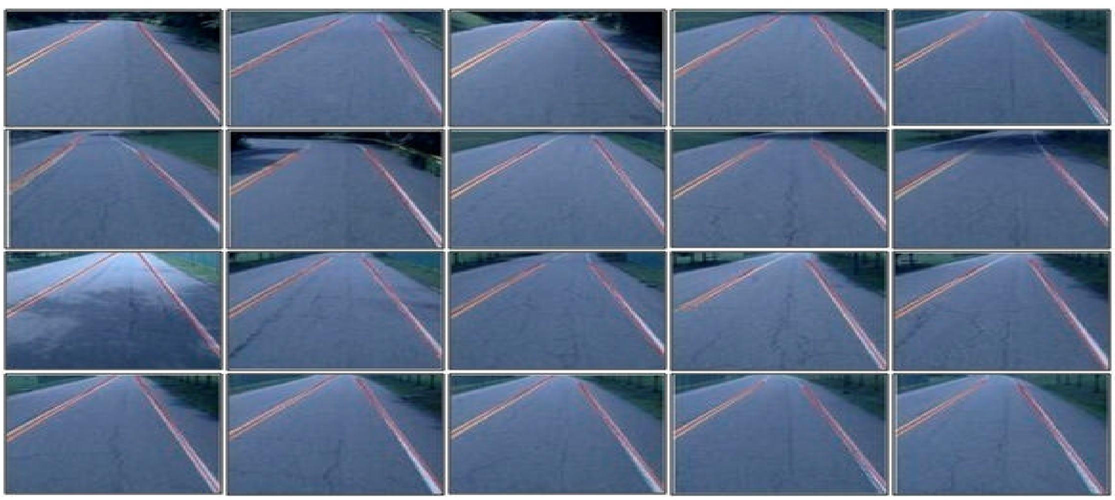


Fig. 9: Lane boundaries detected on the normal view images

dependence of this method on the contrast between lane markings and road, in some cases that the lane markings are totally removed or covered it failed to detect the road region. Also in very sharp curves detecting lane boundaries by using straight lines was not accurate enough.

CONCLUSION

The proposed approach was based on inverse perspective mapping, edge detection and using modified Hough transform to find lane boundaries of the road. The reduction of processing data was obtained by effective selecting of region of interest in the images. The main contribution of this study is introducing a robust model to detect lane boundaries accurately. It can be concluded that this method performed rather well in the presence of shadows and worn lane markings. Both in cloudy and sunny conditions the system worked well and lane markings were extracted accurately. The future work shall focus on dealing with complicated road markings and to come up with some improvements in order to predict the vehicle path on the road. Also the processing time would be reduced by using appropriate filters as well to make the system more compatible for real-time procedure.

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