LANE CHANGE DETECTION AND TRACKING FOR A SAFE-LANE APPROACH IN REAL TIME VISION BASED NAVIGATION SYSTEMS

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ABSTRACT

Image sequences recorded with cameras mounted in a moving vehicle provide information about the vehicle's environment which has to be analysed in order to really support the driver in actual traffic situations. One type of information is the lane structure surrounding the vehicle. Therefore, driver assistance functions which make explicit use of the lane structure represented by lane borders and lane markings is to be analysed. Lane analysis is performed on the road region to remove road pixels. Only lane markings are the interests for the lane detection process. Once the lane boundaries are located, the possible edge pixels are scanned to continuously obtain the lane model. The developed system can reduce the complexity of vision data processing and meet the real time requirements.

KEYWORDS

Edge pixels , lane boundaries, road pixels, linear parabolic lane model.

1. INTRODUCTION

The growing volume of traffic requires higher levels of traffic safety. The aim of the Intelligent Vehicle Systems is mainly that of enhancing driving safety and reducing the driver's workload. The safety of driving cars could be significantly increased by using driver assistance systems which interpret traffic situations autonomously and support the driver. An important component of a driver assistance system is the evaluation of image sequences recorded with cameras mounted in a moving vehicle. Image sequences provide information about the vehicle's environment which has to be analysed in order to really support the driver in actual traffic situations. Our goal is to investigate driver assistance functions not only theoretically but also experimentally. It is expected that machine vision systems can be used to improve safety on the roads, decreasing the number of accidents. Lane detection is crucial to vision-based lateral control as well as lane departure warning for autonomous driving [1]. Since erroneous findings will generate wrong steering commands which may jeopardize vehicle safety, a robust and reliable algorithm is a minimum requirement. However, the great variety of road environments necessitates the use of complex vision algorithms that not only requires expensive hardware to implement but also relies on many adjustable parameters that are typically determined from experience. Most of the researches developed on vision-based systems present limitations in situations involving shadows, varying illumination conditions, bad conditions of road paintings

D.C. Wyld, et al. (Eds): CCSEA 2011, CS & IT 02, pp. 345–361, 2011.

DOI: 10.5121/csit.2011.1231

and other image artifacts. Certain class of lane detection methods [3, 4] relies on top-view (birds eye) images computed from images acquired by the camera. These methods are reliable in obtaining lane orientation in world coordinates, but require online computation of the top-view images (and camera calibration). Deformable road models have been widely used for lane detection and tracking [5–9].Such techniques rely on mathematical models to fit road boundaries. In general, simpler models (e.g. linear) do not provide an accurate fit, but they are more robust with respect to image artifacts. On the other hand, more complex models (such as parabolic and splines) are more flexible, but also more sensitive to image artifacts/noise. Driver assistant system based on computer vision is helpful in relieving the contradiction between enhancement of traffic safety and increment of traffic density. The system can gather information on the environment surrounding the vehicle and detect dangerous conditions. Lane departure detection module is an important part in driver assistance systems and it is used to control the vehicle's lateral position on the road. The location and heading of the vehicle to current lane can be obtained from comparison of steering by the driver and one estimated by an intelligent lateral control system. For lateral control, the most crucial variables to be sensed are the position and orientation of the vehicle relative to the road boundary. In addition to these parameters, sensing of road curvature is quite significant as it facilitates a smooth trajectory. The approaches used to solve this problem exploit the information on road boundaries or lane markings, in which the lateral control depends on lane following and changing. This work focuses on development of vision based lane departure detection.In order to support a driver in a manner which is perceived as unobtrusive and helpful rather than distracting a model-driven approach helps in the determination of the actual traffic situation surrounding the driver.

Various kinds of models are necessary:

1) a model of the behaviour of a vehicle on the road,
2) a model of the overall public road system,
3) a model of a generic geometry of the road visible in front of the vehicle,
4) models for vehicles observable on the road,
5) control-theoretic models for the realization of a complete set of driving maneuvers,
6) a model for how such maneuvers are to be serialized under normal traffic conditions.

With increasing computing power of standard PCs it is possible to realize more complex driver assistance with general purpose hardware as well as to implement more sophisticated algorithms. Two different algorithms are developed to extract measurement points in the image of not only marked but unmarked lane borders as well. Different road types as well as various traffic situations and illumination changes require great care on robustness and reliability. Obstacle information can be used by the system to increase robustness. The algorithm can be extended to track two adjacent lanes. Additionally, classification of marked lane border types based on the already detected measurement points of the lane tracking algorithm can lead to a higher level representation of the road which helps to understand the environmental conditions of the actual situation. Based on this robust video-based lane detection algorithm, lane keeping assistance system can be developed which warns the driver on unintended lane departures. A number of assumptions on driver behaviour in certain situations can be integrated to distinguish between intended and unintended lane departures. The driver assistance functions are based on the detection and tracking of road borders and road markings which is described in the subsequent sections.

2. Literature Survey

Various approaches for lane detection systems have been performed. Dickmanns and Mysliwetz [6] performed a recursive 3-D road and relative vehicle's motion behaviour recognition using four

Intel 80286 and one 386 microprocessors. On the other hand, Leblanc et al.[7] created an automatic road-departure warning system called CAPC by using two Kalman filters to estimate vehicle state and both local and previewed road geometry information. Besides, Kreucher and Lakshmanan [8] presented a LANA system to extract lane markings in frequency domain and to detect lane with a deformable template. Bertozzi and Broggi[3] presented a GOLD system using stereo inverse perspective mapping. Kaszubiak et al.[10] used two CMOS cameras to measure the disparity map locating road objects and detect the lane position using a Hough transform. Wu et al.[11] presented an adaptive lane departure warning system operating in frequency 600-MHz processor by detecting lane markings. Yeh and Chen[12] developed a vision-based lane and vehicle detecting system by enhancing lane markings and locate left-right boundaries. Jeng et al.[13] presented a real-time mobile lane detection system using generic 2-D Gaussian smoothing filter and global edge detection. Pankiewicz et al[14] performed a simple canny detector and linear Hough Transform to locate lane boundaries. Apostoloff and Zelinsky proposed a lane tracking system based on particle filtering and multiple cues. In fact, this method does not track explicitly the lanes, but it computes parameters such as lateral offset and yaw of the vehicle with respect to the center of the road. Although the method appears to be robust under a variety of conditions (shadows, different lighting conditions, etc.), it cannot be used to estimate curvature or detect if the vehicle is approaching a curved part of the road. McCall and Trivedi proposed a method for lane detection using steerable filters. Such filters perform well in picking out both circular reflector road markings as well as painted line road markings. Filter results are then processed to eliminate outliers based on the expected road geometry and used to update a road and vehicular model along with data taken internally from the vehicle. Such technique is robust with respect to lighting changes and shadows, but has shortcomings for relatively curved roads (because this method relies basically on a linear model). LeBlancetal. [7] proposed a road-departure prevention system, that predicts the vehicles's path and compares such path with the sensed road geometry to estimate the time to lane-crossing (TLC). However, the vision-based sensor requires good lighting and pavement conditions to detect lane boundaries. Risacketal proposed a lane keeping assistance system, which warns the driver on unintended lane departures. Infact, they used an existing video based lane detection algorithm and compared different methods to detect lane departure, using several assumptions on driver behaviour in certain situations to distinguish between intended and unintended lane departures. Lane departures are successfully detected, by their technique, but they also needed roads in good conditions and lighting conditions. Lee proposed a lane departure detection system that estimates lane orientation through an edge distribution function (EDF), and identifies changes in the travelling direction of a vehicle. However, the EDF may fail in curved roads with dashed lane markings. A modification of this technique [15] includes a boundary pixel extractor to improve its robustness. However, curved lanes may still cause problems, because a linear model (computed using the Hough transform) is used for fitting lane boundaries. The AURORA system applied a binormalized adjustable template correlation technique using downward looking cameras. However, it worked well only for slowly-varying roads.

3. Methodology

3.1. System design

The system consists of four subsystems: the sensor (videocamera), image processing, the controller and the vehicle as shown in Fig1.

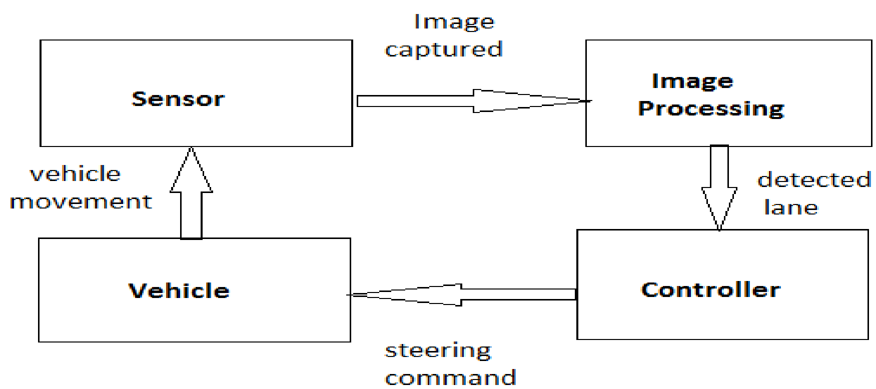

Fig.1.The four subsystems of a vision-based autonomous vehicle driving control system.

3.1.1. Sensor

The sensor is the key element of an autonomous vehicle system, because it provides the information about a driving scenario. The system discussed here uses a single video camera as a sensor. To get the input data from the image, the video image sequences must be captured. The input data of this system is provided by colour image sequences taken from a moving vehicle. A single colour video camera is mounted inside the vehicle behind the wind shield along the central line. This records the images of the environment in front of the vehicle, including the road, the vehicles on the road, traffic signs on the roadside and, sometimes, incidents on the road. The video camera saves the video images in AVI file format, then the video file is transferred to the computer. The image processing subsystem takes an image from the memory and starts processing it in order to detect the desired lane.

3.1.2. Image Processing and Analysis for Predicting and Detecting the vehicle lane

The goal of the image processing is to extract information about the position of the vehicle with respect to the road from the video image. Two major processes are implemented: the pre-processing process and then the lane detection process. The goal of pre-processing is to remove image noise and make the images sharper. The goal of lane detection is to detect the desired lane of the vehicle in order to obtain the look-ahead distance and the lane angle. This process is based on the real-time data of video sequences taken from a vehicle driving on the road. The four processing steps of the lane detection algorithm are image segmentation, edge detection, Hough Transform, and lane tracking as shown in Fig.2.

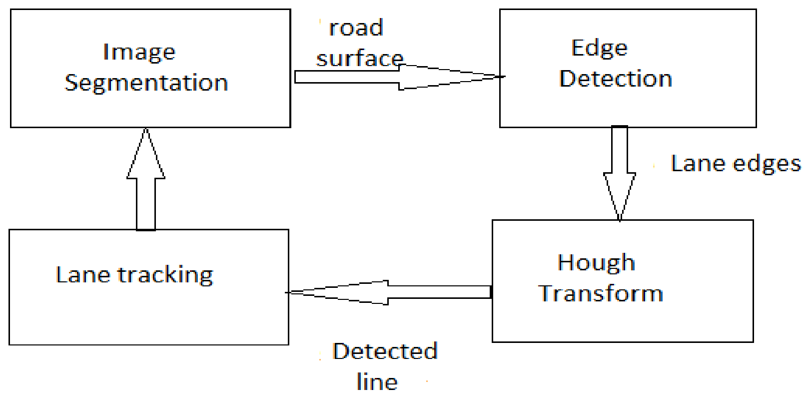

Fig. 2. Image processing steps of the lane detection algorithm.

3.1.3. Regions of interest measurement and features extraction using Colour Cue segmentation

Segmentation of the images is crucial for the analysis of the driving environment. Parts of the traffic scenes can be recovered by extracting geometric features in order to infer and verify the existence of certain categories of objects. Another relevant method of segmentation is based on region growing and clustering. The effectiveness of such a method crucially depends upon the capability of measuring similarity, such as in texture and pixel colour information. A colour-based visual module provides relevant information for localization of the visible road area, independently of the presence of lane boundary markings and in different lighting conditions. In the road image, the road area has characteristics such as the following: 1) most of the lower part of the image was considered as the road area, and 2) road areas have a quasi-uniform colour, resulting from the fact that the road area is generally a grey surface in a more coloured environment. Although the absolute surface colour can provide useful cues for this task, the response of the colour imaging device is mediated by the colour of the surfaces observed, by the colour of light illuminating them, and by the setting of the image acquisition system. To have better control over variations in pixel values for the same colour, and to remove the shadows, the RGB colour space must be converted to the HSV (hue, saturation and value) colour space. Fig.3. shows the image by image segmentation process by computing the coordinates of regions of interest and determining the pixel colour of interest. Fig. 4. shows the lane marking extraction based on the colour of pixels of interest.

Fig. 3. Road surface as the object/region of interest. Other objects/background are converted to black (0).

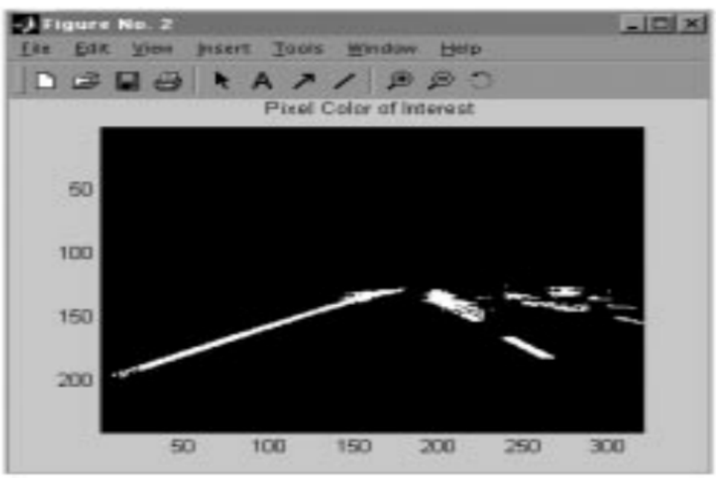

Fig. 4. Lane marking extraction based on the colour of pixels of interest.

3.1.4. Extraction and detection of vehicle lane edges using the edge detectors

The purpose of the edge detection process is to extract the image edges using an edge detection operator or an edge detector. The operator will locate the position of pixels where significant pixels exist. The edges are represented as white and non- edges will be black. Fig.5. shows the lane edges of the image. Edges in images are areas with strong intensity contrasts. Edge detecting of an image significantly reduces the amount of data and filters out useless information while preserving the important structural properties of the image. Edge detection is the most common approach for detecting meaningful discontinuities in the grey level. Intuitively, an edge is a set of connected pixels that lie on the boundary between two regions. It is important that edges occurring in an image should not be missed and that there is no response to non-edges. The second constituent is that the edge points are well localized. In other words, the distance between the edge pixels as detected by the detector and the actual edge is to be minimal. A third is that there is only one response to a single edge.

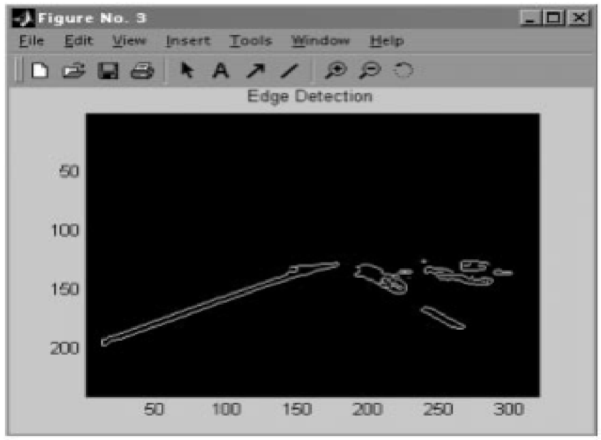

Fig. 5. Edges of lane marking and some unwanted edges.

3.1.5. Features isolation and approximation of the vehicle lane using Hough Transform

Hough Transform was used to combine edges into lines, where a sequence of edge pixels in a line indicates that a real edge exists. By using the edge data of the road image, Hough Transform will detect the lane boundary on the image. This is because this technique detects shapes from image edges, and assumes that primitive edge detection has already been performed on an image. This technique is most useful when detecting boundaries whose shape can be described in an analytical or tabular form. The key function of this system is to map a line detection problem into a simple peak detection problem in the space of the parameters of the line. Hough Transform is a technique that can be used to isolate features of a particular shape within an image. It can be divided into two types: classical and generalized. Because it requires the desired features to be specified in some parametric form, the classical Hough Transform is most commonly used for detection of regular curves, such as lines, circles, ellipses, etc. A generalized Hough Transform can be employed in applications where a simple analytic description of a feature is not possible. Hough Transform works by letting each feature point (x, y) vote in (m, b) space for each possible line passing through it. These votes are totalled in an accumulator. If, for instance, a particular (m, b) has one vote, this means that there is a feature point through which this line passes. If it has two votes, it means that two feature points lie on that line. If a position (m, b) in the accumulator has n votes, this means that n feature points lie on that line. The algorithm for the Hough Transform can be expressed as follows:

1. Find all of the desired feature points in the image.
2. For each feature point: For each possibility i in the accumulator that passes through the feature point, increment that position in the accumulator.
3. Find local maximum in the accumulator.
4. If desired, map each maximum in the accumulator back to the image space.

3.1.6. Lane tracking

A distinction can be made between the problems of lane detection and tracking. Lane detection involves determining the location of the lane boundaries in a single image without strong prior knowledge regarding the lane position. On the other hand, lane tracking involves determining the location of the lane boundaries in a sequence of consecutive images, using information about the lane location from previous images in the sequence to constrain the probable lane detection in the current image. In each second, the first several image frames will be processed by the lane detection algorithm, and this will provide a good estimate of lane tracking for the next frames. Kalman filter is used to predict the model parameters.

4. Camera Calibration

The system detects lane markings using a monochromatic CCD camera mounted behind the windshield. Preferred position of the camera is behind the rear view mirror in order to get a clear view through the windshield as shown in figure 6. The first frame acquired by the camera is processed, and the two (left and right) lane boundaries are obtained automatically. Our coordinate system coincides with image coordinates, and a threshold xm separates the near and far vision fields. The choice for xm depends on the size of the acquired images and the tilt angle of the camera, and should result in a length of about10m for the near field (in a typical camera installation with resolution of 240 by 320pixels, it is possible to see about 30 – 40 m ahead with a reasonable definition).

Fig.6. Experimental set up .

5. Initial lane detection

For the initial detection, a linear model for the lane boundary is chosen, because of its simplicity and robustness. We also assume that the following conditions are satisfied in the first frame of the video sequence:

a) the vehicle is initially located in a straight portion of the road;

b) the vehicle is approximately aligned with the road;

c)there are no significant linear structures in the image, except for the lane boundaries.

To detect the linear lane boundaries, EDF approach is adopted combined with the Hough transform.

5.1. The edge distribution function

For the greyscale image I(x,y), the gradient function del I(x,y) can be approximated by:

$$\nabla I(x, y) = \left(\frac{\partial I}{\partial x}, \frac{\partial I}{\partial y}\right)^T \approx (D_x, D_y)^T,$$

where D_x and D_y are differences computed in the x and y directions (this differences can be computed using the Sobel operator).We can estimate the gradient magnitude and orientation using the following equations:

$$|\nabla I(x, y)| \approx |D_x| + |D_y|, \quad \theta(x, y) = \tan^{-1}(D_y/D_x).$$

To determine the orientation of the road boundaries, we compute the edge distribution function (EDF), which is the histogram of the gradient magnitude with respect to the orientation. To compute this histogram, the angles θ(x, y) within the range [-90, +90] were quantized in 90 subintervals. Considering that lanes are the only significant linear objects in the image, and that the car is aligned with the central axis of the road, it is expected that lane boundaries will generate two local maxima in the EDF. However, multi-lane roads generate several local maxima. Infact, the figure illustrates a road with three traveling lanes (and the vehicle is located in the middle lane). Fig.7. illustrates the EDF for this image, and four local maxima can be observed. The first one (at θ= -36) is related to the right boundary of the central lane; the second one (at θ= -14) is related to the right boundary of the right lane; the third one (at θ= 12) is related to the left boundary of the left lane; finally, the last one (at θ= 28) is related to the left boundary of the central lane.

In general, inner lane boundaries (where the car is travelling) have approximately symmetric orientations and are closer to vertical lines in the image (i.e. correspond to smallest and largest values of θ in the EDF). If α1 and α 2 denote the smallest and largest orientations of the EDF, respectively, then they are kept if

$$|\alpha 1 + \alpha 2| < T1$$

where T1 is a threshold. Let α be the orientation corresponding to the desired lane boundary. Also, let g(x, y) be the directional edge image. It should be noticed that g(x, y) contains edge magnitudes of the original image I(x, y) that are aligned with the direction α. These magnitudes will be mostly related to the lane boundary, but some pixels related to noise or other structures that are aligned with the lane may also appear. Fig.8 shows image g(x, y) for α = -36 , which corresponds to the right lane boundary. Indeed, some isolated pixels with small magnitude that are not related to this lane boundary appear in the image.

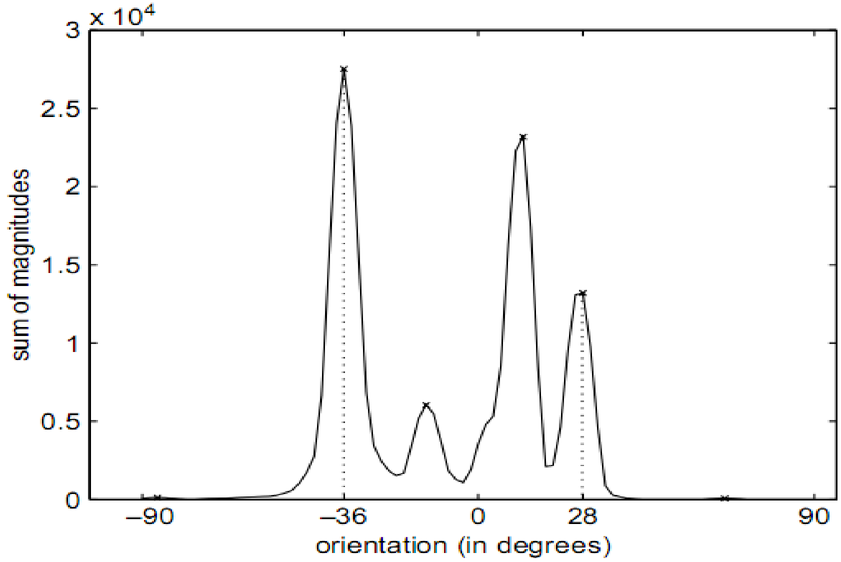

Fig.7. Smoothed edge distribution function.

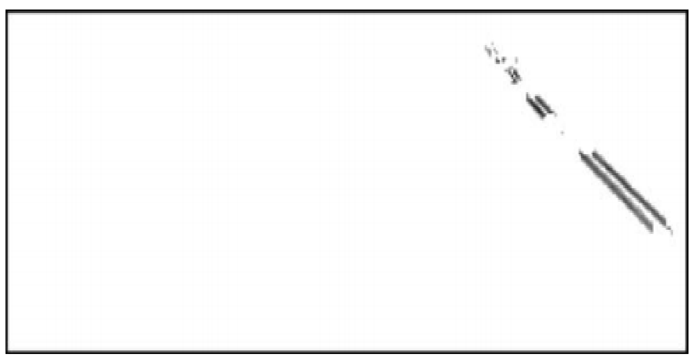

Fig.8. Magnitudes aligned with the right lane boundary.

Applying the Hough transform to a set of edge points (xi,yi) results in a 2Dfunction $C(\rho, \theta)$ that represents the number of edge points satisfying the linear equation $\rho = x\cos\theta + y\sin\theta$. In practical applications, the angles θ and distances r are quantized, and we obtain an array $C(\rho, \theta)$. The local maxima of $C(\rho, \theta)$ can be used to detect straight line segments passing through edge points. In our case, the orientation θ can be obtained from the EDF peak.

This line detection procedure is applied independently to each lane boundary, resulting in one linear model for each boundary. This initial detection is used to find the lane boundary region of interest (LBROI), which will be the search space for lane boundaries in the subsequent frames of the video sequence. The LBROI is obtained by 'thickening' the detected lane boundary ,such that it is extended w(x) pixels to the right and w(x) pixels to the left in the y direction. Due to camera perspective, LBROIs should be thinner at the top of the image (farfield), and fatter at the bottom(nearfield). A simple choice for w(x) is a linear function, stretching w_{bottom} pixels to both sides at the bottom and w_{top} pixels at the top. The LBROIs shown in Fig. 9.

Fig.9. LBROIs corresponding to initial lane segmentation using the linear model.

6. Estimation of Additional Lanes

In order to extract more information from each image, the two lanes adjacent to the current(main)lane are estimated as well. The same model and the same measuring method as for the main lane is applied to perform this task. Some parameters of the neighbour lanes are assumed to be identical with the main lane, as the yaw angle and the curvature parameters. These parameters are not estimated for the neighbour lanes. The pitch angle is used to check the plausibility of the neighbour lanes. If the pitch angle difference between a neighbour lane and the main lane exceeds a threshold, the neighbour lane estimation is rejected.

7. Classification of Marking Lines

Marked and unmarked lane borders are distinguished during the detection of measurement points. A marked lane border can appear differently, e.g., as solid or as dashed marking line. Solid and dashed marking lines can be distinguished by analyzing gaps between the measurement points. The measurement points are sorted with ascending corresponding distance in world coordinates. When a solid marking line is tracked, there will be measurement points on almost every scan line. On dashed marking lines, some scan lines will have no measurement point. The gap size between two successive measurement points is computed in world coordinates by the difference of the look ahead distances corresponding to the measurement points. If the maximal gap size in the world for one lane border exceeds a threshold, the border is classified as a dashed marking line, otherwise it is classified as a solid line.

8. Situation Analysis

It is important to clearly determine when a warning should be issued. Therefore, situations are to be defined which are parameterized with the lane geometry and the driving maneuver. There are three possible lane geometries: “straight,” “leftbend,” and “rightbend.” Each of them can be combined with the driving maneuvers “keeping the lane,” “leaving the lane to the left,” and “leaving the lane to the right” resulting in certain basic situations our warning system has to cope with.

In the situation “keeping the lane,” clearly, no warning should be given, regardless of the form of the lane. In the cases “leaving the lane,” warnings should be issued only when the lane is left unintentionally. It is necessary to monitor the behaviour of the driver to detect intentional lane leavings. Situations with intentional leaving are :

1) lane changes,
2) corner cuts,
3)evasive maneuvers in emergency cases.

Warnings in these situations are regarded as false warnings (falsepositive). To achieve a high user acceptance of the system, no false positives are allowed. Important states of the car which enable to monitor the driver intentions are

1) blinker state(off, left, right),
2) braking,
3) steering angle.

These information can be easily obtained from a car network, e.g. aCAN-bus.

8.1. Intended Leaving

To avoid false warnings during intended lane departures, additional information is necessary. Consider the following intended departures:

1) lane changes which are announced by the driver using the blinker,
2) emergency maneuvers with brake and high steering activity,

Before changing a lane, drivers are obliged to set the blinker to the according direction. So, if the blinker is set while departing the lane, warnings are suppressed. If the driver brakes he already reacts to some situation and is most likely aware of the situation. Additional warnings would be disturbing in such cases and are, therefore, suppressed. The same argument holds if there is a high steering activity. Drivers who cut corners surely will not accept a system that warns in such situations.

9. Vehicle's Current Position.

The easiest way to detect the departure of the lane is to check the car's current position(CCP)in the lane. The position is estimated by the lane detection algorithm. The lateral offset y_0 denotes the distance between the center of the lane and the center of the car. Since the gear angle is small, the car is approximately parallel to the lane. With the given car width bc, the position of the front wheels relative to the lane borders can be computed by the equation

$$\Delta y = \frac{b}{2} - \left(y_0 + \frac{bc}{2}\right)$$

$$\Delta y = \frac{b}{2} + \left(y0 - \frac{bc}{2}\right)$$

The current lane width b is also estimated by the lane detection algorithm. The upper and lower line of the equation correspond to the position of the right and left wheel relative to the right and left lane border, respectively. The car is inside a lane when both front wheels of the car are still inside the lane. This is the case when $\Delta y > 0$ in both cases. No warnings are necessary here. As soon as one wheel crosses the lane border on its side, the car leaves the lane, then, $\Delta y < 0$ on the corresponding side of the lane. Whether a warning is necessary or not depends on the driver's intention.

10. Departure estimation

If the vehicle is traveling in a straight portion of the road and stays at the center of the lane, we should expect symmetry (for the near vision field) in the orientations of left and right lane boundaries ,as depicted in Fig.10.If the vehicle drifts to its left, both θ_l and θ_r increase. If the vehicle drifts to its right, both θ_l and θ_r decrease. In any case, the value of magnitude of θ_l plus θ_r gets away from zero. Thus, a simple and efficient measure for trajectory deviation is given by:

$$\beta = | \theta_l + \theta_r |$$

If β gets sufficiently large, the vehicle is leaving the center of the lane. In this work, β is compared to a threshold T3, and a lane departure warning is issued if β >T3. Experimental results indicate that T3=15 degrees is a good choice, coinciding with threshold T1 used in the initial lane detection algorithm.

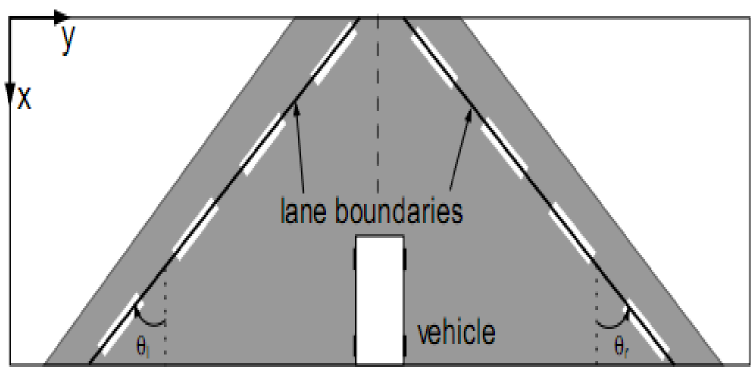

Fig.10. Orientation of lane boundaries.

11. Feature extraction

In lane hypothesis generation step, lane-mark edge features like edge-orientation, edge-length, and edge-pair width are checked to filter out noise edges and select candidate lane-mark edges. For lane hypothesis verification, lane-mark colors are checked inside regions enclosed by candidate lane-mark edge-pairs.

Generally there are three kinds of lane-mark colors: white, yellow and blue. These three colors are much easier to identify in the YUV color space compared to the commonly used RGB color space. Therefore, the color checking step is done in the YUV color space. The first thing is to transform the RGB color space into the YUV color space using the equation,

$$\begin{vmatrix} Y \\ U \\ V \end{vmatrix} = \begin{vmatrix} 0.299 & 0.587 & 0.114 \\ -0.169 & -0.331 & 0.500 \\ 0.500 & -0.419 & -0.081 \end{vmatrix} \begin{vmatrix} R \\ G \\ B \end{vmatrix}$$

Then the yellow-checking image is produced by U subtract by V, the blue-checking image is generated by V subtract by U. White is checked by using the Y channel. The result is shown in the Fig.11. By using adaptive thresholds, yellow, blue, and white dominant regions can be extracted from the corresponding color checking channels.

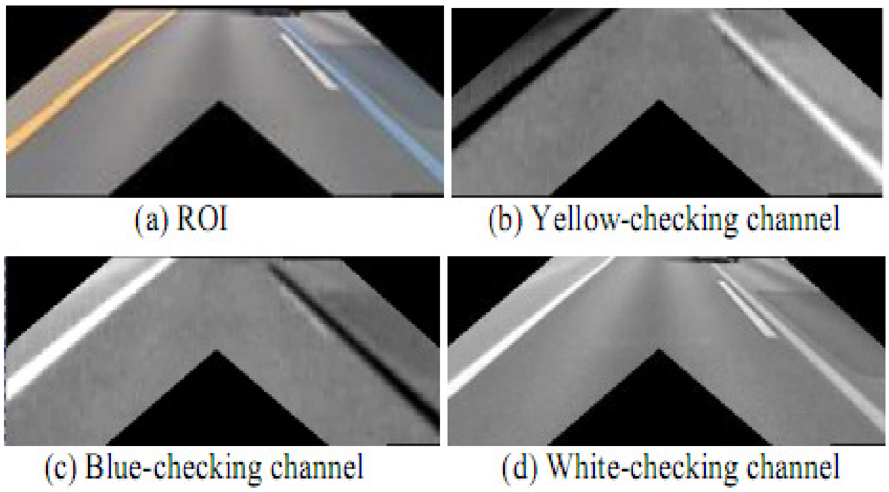

Fig.11. Channels used for color checking.

13. Limitations

The main limitation of the proposed technique is regarded to significant occlusions of lane markings due to vehicles in front of the camera as shown in fig.12. In fact, significant occlusions occur only when the vehicle in front is very close to the camera (lessthan10m), which typically happens only in traffic jam situations. Although the linear-parabolic model performs well in the presence of sparse shadows (such as irregular shadows cast by trees), it may present erroneous results if strong aligned shadows appear close to lane markings. In such cases, edges introduced by shadows may be stronger than edges related to lane markings, specially in dashed markings**.**

(a) (b)

Fig.12. Limitations of the proposed technique. (a) Occlusion of lane markings. (b) Strong shadow causing an erroneous detection of lane boundaries.

14. CONCLUSIONS

In this paper, a robust lane detection method has been developed which utilize the human visual properties of lateral inhibition, far-near adaptation, and joined the mutual support in feature extraction. This approach for safe lane systems has developed a safety system for avoiding lane departures for a large and complex set of traffic scenarios. Vehicles with complete lane keeping support systems can be introduced with the help of active steering. Other driver assistance applications such as lateral cruise control and collision avoidance can also be included along with lane keeping support systems. According to the experimental results with the proposed methods in the paper, we can summarize the following points:

(1) This system can be used under most of environments in the daylight, night time, sunny and raining day.
(2) This system can be used under various lane-markings and vehicles for lane boundary recognition and preceding vehicle detection.
(3) In various environments, the system can provide high availability, reliability and accuracy in lane deviation and headway distance estimation.
(4) The image-processing rate of the system is more than 20 fps (frame per second), and it meets the requirements of real-time computing in an embedded system.

Based on a single CMOS camera mounted on the windscreen, the system can recognize lane boundary and preceding vehicle by means of image processing and provide the lane departure warning and forward collision warning functions. In lane departure detection, gray scale statistics, dynamic range of interesting (ROI) and featured-based approaches are applied to recognize the lane boundaries and road geometry model is used to detect the lane departure. In addition, the driver assistance system has taken convenience installation into consideration. By simplifying the installation steps, the system can be adaptive to most of vehicles.

15. ACKNOWLEDGEMENTS

We would like to express our sincere gratitude to Dr. T.N. Padmanabhan Nambiar, Head of Department, Electrical and Electronics Engineering for providing us affectionate guidance.

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