Detection and Classification of Road Lanes with a Frequency Analysis

Juan M. Collado, Cristina Hilario, Arturo de la Escalera and Jose M. Armingol

Abstract—**This paper presents a Road Lanes Detection and Interpretation algorithm for Driver Assistance Systems (DAS). The algorithm uses an edge filter to extract lane borders to which a straight lane model is fitted. Next, the lane mark type (continuous, discontinuous or merge) is recognized using a Fourier analysis. The line type is essential for a robust DAS. Nevertheless, it has been seldom considered in previous works. The knowledge of the line types of the road helps to guide the search for other lines, to automatically detect the type of the road (one-way, two way or highway), and to tell the difference between allowed and forbidden maneuvers, such as crossing a continuous line. Furthermore, the system is able to auto calibrate, thus easing the process of installation in commercial vehicles.**

Index Terms—**Driver assistance systems, Image processing, Intelligent transportation systems, Machine vision, Object detection, Road vehicles.**

I. Introduction

ROAD vehicles play a very important role in transportation systems, which have brought out several problems: traffic jams, accidents, environment degradation, etc. The goal of the Intelligent Transportation Systems is to increase security, efficiency, and comfort of the transport, by improving the functionality of cars and roads with the use of information and communication technologies. In this paper the Road Detection and Interpretation module of the IVVI (Intelligent Vehicle based on Visual Information) project is presented.

A. The IVVI Proyect

IVVI (Fig. 1) is a research platform for the implementation of systems based on computer vision, with the goal of building an Advanced Driver Assistance System (ADAS). It consists of three modules:

1) Anti-collision: The driver is warned about the presence of vehicles or pedestrians on the road.

2) Speed supervision: A warning signal is fired when the vehicle runs at a dangerous speed. This depends on the road type, the position and the speed of other vehicles, and the road shape.

3) Overtaking assistant: The blind spot is scanned for possible cars in the adjacent lane, and the left line is checked to be discontinuous.

These modules are supported by five sensing capabilities, namely: traffic signal detection, vehicle detection, pedestrian detection, road detection, and blind spot perception.

IVVI is equipped with a DC/AC power converter connected to the vehicle's battery. Through it, the electrical power needed for the computers and cameras is got. There are two PCs in the vehicle's boot which are used for processing of the images grabbed by the cameras. There is an electronic multiplexer for the video, mouse and keyboard signals. Thanks to it, the human operator, placed on the back seat, is able to work with two systems simultaneously. There is a trinocular stereo vision system. As the cameras are progressive scan, they can capture images on movement and avoid the problems associated with interlace video. There is a color CCD camera for the detection of Traffic signs and another vertical signs.

The purpose of the Road Detection and Interpretation capability is to calculate automatically the lanes position respect to the car, the lanes boundary type (continuous, discontinuous or merge), and finally the road type (one-way, two-way or highway). The latter can only be guessed from the number of lanes and the line types.

In addition, this module has to interact with other modules, especially with the vehicle detection one [1]. Lane position helps vehicle detection by giving an idea of the regions of the

Fig. 1 (left) IVVI vehicle; (top right) detail of the trinocular vision system; (bottom-right) detail of the processing system

Manuscript received December 14, 2004. This work was supported in part by the Comunidad de Madrid through the project 07T-0018.

All authors are with the Department of Intelligent Systems and Automation of the Universidad Carlos III de Madrid, Spain (e-mail: {jcollado, chilario, escalera, armingol}@ing.uc3m.es).

image susceptible of containing a vehicle, and the estimated size of the vehicle depending of the image position, which is related to the distance to the camera. It also helps to know if a vehicle is likely to be oncoming or out-coming depending on the lane where it is placed on and the road type. Finally, the vehicle detection module can help the lane detection module to avoid analyzing the areas of the image occupied by other vehicles.

B. *Previous work*

So far, lane detection has already been investigated for more than two decades. Some impressive results have already been demonstrated under real conditions [2][3][4], specially in the topic of automatic driving. Nevertheless, at the present time, research is moving towards driver assistance systems, because of the legal and psychological difficulties of an automatic system. Today, even though many car manufacturers have expressed the intention to include vision-based DAS in the short term, there are still very few commercial DAS available for commercial cars. It can be said that though many problems have been solved yet, there is still a need to increase the robustness of these systems so that they can be useful for drivers.

Road detection algorithms for marked roads can be classified in two groups:

1) Model-based methods follow a top-down approach. Their main advantage is that the lane can be tracked with a statistical technique, thus, false detections are almost completely avoided. However, as they follow a top-down approach, only the characteristics included in the model are found. Therefore, it is difficult to build a model that is able to adapt to new road or environment conditions.

2) Feature based methods follow a bottom-up approach. Unlike model-based methods, it is difficult to apply statistical techniques for lane tracking. However, all the characteristics that are present in the image are subject to be found. This work follows, so far, a bottom-up approach, because of the need to interpret the road environment image depending on all present road line marks.

Moreover, most of the actual research effort moves towards adjusting high order models to the lane shape. The goal is to extract accurate information, overcoming the instabilities and noise sensibility typical of more complex models such as the 4D [5] and zero-bank [6][7]. LOIS algorithm [8] fits parabolas to the lane boundary markings. Afterwards, the LANA algorithm [9] system tries to get a better adjustment in the far region through the use of a frequency based filter. Examples of higher order models are [10] which models horizontal curvature as a cubic, and tracks the lane with an enhanced CONDENSATION algorithm [11], and in [12] the horizontal curvature of the road shape is modeled as a third order polynomial, and the vertical curvature as a second order polynomial. Other works try to adjust splines [13] or snakes [14], but these are more difficult to track.

It seems that there are few works on road marking lines classification and road type recognition, although this information is essential for a Driver Assistance System. Few works consider the existence of other lanes, which is directly related to the road type. The direction of vehicles on other lanes, the possible maneuvers and the speed limit, are just some examples of facts that depend on the road type.

In [15] a six parameter model that fuses shape and structure is used. The shape is modeled as a second order polynomial, and the structural model considers the lane mark as a square waveline, with its period, duty cycle and phase. The parameters can be tracked from frame to frame, but the algorithm requires an initialization step that is very time consuming. Besides that, only one lane boundary mark is fitted to each frame. [16] roughly classifies the marks as solid or dashed, by analyzing the gaps between the measurement points. If the gap exceeds a threshold the mark is classified as dashed. Thus, the algorithm can easily be confused with any obstacle or structured noise that occludes the marking line, such as shadows or other vehicles. [16] also tries to estimate the left and right directly adjacent lanes assuming that some of their parameters are identical to the central lane. [17] maintains an array of probabilities defining the presence of lateral lanes. The lanes are numbered, and another array stores the identification number of the lane in which the vehicle is traveling.

In short, these methods can detect any number of lanes, but someone or something has to indicate to the algorithm how many lanes to search for, and where (to the right or to the left). That is, there is a need of an external technique that indicates to the algorithm how many lanes to search for, and where they can be located (right or left). The difficulty arises from using a top-down approach without taking into account the lane marking type.

II. ROAD LINES DETECTION

The image analysis can be done in two reference systems. That is, from the car-view image, e.g. [8] (Fig. 2) and from a bird eye-view after a perspective transformation [18], assuming that the world is flat (Fig. 4-a). The latter is the option chosen in this work, which has the advantage of facilitating the detection of the marked lines and the integration of temporal information, but presents calibration problems. If the extrinsic calibration parameters of the vision system (its position and orientation in world coordinates), are not well calculated, the flat road assumption is violated, and the bird-eye view image will show converging or diverging lines, instead of parallel ones. This leads to a bad calculation of the lane position and orientation. To overcome these problems, an auto calibration algorithm based on evolutionary

Fig. 2: On-board camera-view

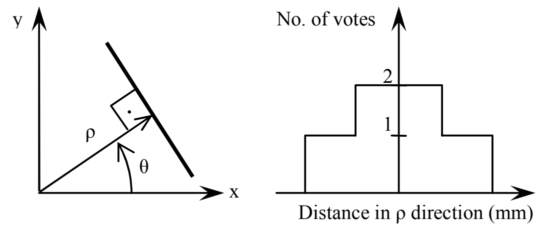
techniques is being tested on the IVVI vehicle. This algorithm uses road lane markings as a calibration pattern, and only requires the vehicle to grab a frame of a flat and straight section of the road. A more detailed explanation can be found in [19].

Usually, the recognition of an object in an image has two stages. First, the relevant characteristics of the image are enhanced, and second a model is adjusted. This lane detection algorithm is designed to work in painted roads, outside of cities; therefore, in this case the relevant characteristics are the edges of the objects in the image.

A. Preprocessing

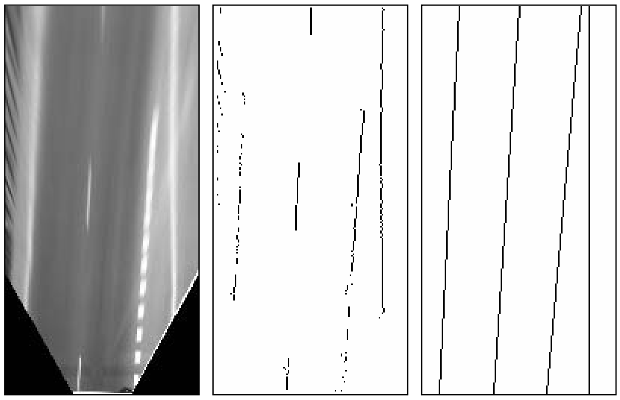
The preprocessing step extracts from the original image the pixels that are candidates to belong to a road line. Road lines are usually modeled as bright bands over a darker background. As the lane curvature is small in the nearby region of the road, these lines are mainly vertical in the bird-eye view image of the road. Therefore, the search for road mark candidates consists of looking for dark-bright-dark transitions in the horizontal direction.

The borders of the image are extracted with a spatial filter based on the ideas of the Canny border extractor. The Canny filter offers a good signal-noise ratio, compared to other border extractors. This is important because the border image will be used in the frequency analysis that identifies the road line type, therefore, this image should be as noise clean as possible. This filter is optimized for speed and uses the intermediate steps of the Canny filter to estimate the orientation of the border. This way, the borders that are not essentially vertical are discarded.



(a) (b)

Fig. 3 (a) Hough parameterization; (b) Voting kernel shape



(a) (b) (c)

Fig. 4 (a) Remapped image; (b) Mark candidates image; (c) Lines detected by modified Hough Transform.

Moreover, a line painted on the road has a right and left border which in the border image is reflected in two close borders with opposite gradient directions. So, once the borders are extracted, the algorithm scans the border's image line by line, matching pairs of borders that are within a certain range of distances, and then, it returns the middle point of the pair. This range of distances limits the possible widths of the road lines. Actually, the width is considered to be within 10 and 40 cm (1 and 4 pixels, respectively).

B. Line Detection

Next, a lane border model must be fitted to the observations. Many line borders models have been previously used in the literature. In this article, a straight line model is extracted. Although this model gives a poor description of the road shape, it has several advantages. Straight lines can be robustly and quickly extracted with the Hough Transform, a technique that can hardly be applied to more complex models in real time. It also facilitates a lot the process of auto-calibration, and line type classification. Besides, this model fits quite well to the road lines in the nearby region of the road.

Compared to other model fitting methods, the Hough Transform is very robust as it uses global information, then, it can easily detect the road lines even though they are discontinuous or partially occluded. In addition, when the model is simple and the image is small in size, it is fast enough to be applied in real time.

C. Enhancements of the Hough Transform

It has been demonstrated in [20] that the best Hough kernel shape is a Gaussian function. In [21] this kernel shape is compared in performance with the "hat" function, concluding that a gaussian-shaped kernel generates more abrupt peaks in the accumulator space, thus easing the line detection. However, this requires operating in floating-point mode, which is computationally expensive. For that reason, a rough, but faster and accurate enough approximation is used (Fig. 3-b). This kernel is applied in the ρ direction, according to the parameterization depicted in (Fig. 3-a).

In order to refine the Hough Transform output, instead of directly taking the parameters of the most voted lines, these parameters are calculated as a weighted sum of the parameters that lie within a square region of the Hough accumulator, centered in the peak. The peak corresponds to one of the most voted lines, and the weight is the number of votes for each cell of the Hough accumulator, within the square region. This step allows relaxing the resolution of the sampling of the accumulator space, without losing precision in the parameters of the detected lines.

Again, as the road lines are mainly vertical, the Hough accumulator is limited in angle. This avoids being interfered by other features on the image, and it speeds up the computation. The allowed angle range goes from –15 to +15 degrees. In addition, all the trigonometric functions are implemented as look-up tables.

III. ROAD LINES CLASSIFICATION

The extracted lines are classified in the different types that are found on roads. The main difficulty of this task is the lack of international standardization about the length and frequency of the white stripes in dashed lines. However, most roads have three basic line types, namely: continuous, discontinuous and merge.

The intensity line profile for each detected line (right column of Fig. 5) is not a good data to feed the frequency analysis, because its appearance changes substantially with the environment conditions. Besides, the resolution of the bird-eye view in the distance is poor. This is an inconvenience with the merge lines, which appear blurred far ahead and could even look like a continuous one (Fig. 5-a). Besides, the power spectrum (left column of Fig. 5) presents a tiny peak at the specific frequency.

It is more robust to obtain the line profile from the thresholded image given by the preprocessing step (Fig. 4-b), which is showed on the left side of Fig. 6. Again, the right side of the figure depicts the power spectrum of Fast Fourier Transform applied to the line profile vector. The results show that a clear sharp peak appears in the Fourier Transform power spectrum when the line is dashed, and that the value of the frequency associated to that peak gives the line type (discontinuous or merge). These peaks are depicted on the left side of Fig. 6-a and Fig. 6-b with arrows pointing at them. No significant peaks are present when the line is continuous (Fig. 6-c). It can be seen that, now, the peaks are sharper and much easier to detect. It has been heuristically found that only the first 21 frequencies are significant in this analysis.

Thus, the classification is performed by scanning the first 21 frequencies. Two requisites are needed in order to classify a line as discontinuous or merge:

1) In the first place, a peak must be found within a certain range of frequencies. Two different frequency ranges have been specified. The dashed vertical lines on the left side of Fig. 6-a and Fig. 6-b show the limits for merge and discontinuous lines, respectively.

2) In the second place, the peak must exceed a threshold, which depends on the frequency interval, as the height of the peak decreases as the frequency increases. On the left side of Fig. 6, an horizontal line depicts the threshold for each frequency interval. Fig. 6-c shows that no peak exceeds the threshold in neither of the specified frequency ranges when the line is *continuous*.

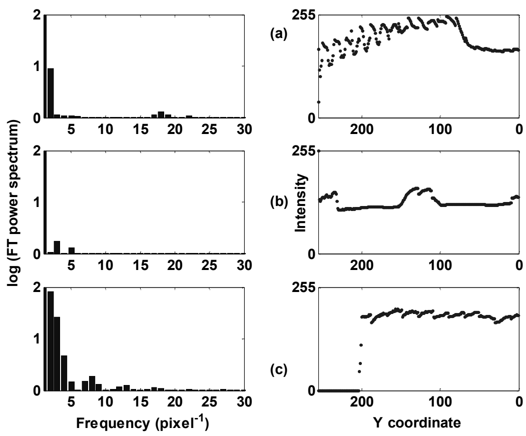


Fig. 5 (right) line profile extracted from the intensity image (Fig 4-a)
(left) Power spectrum of the Fourier analysis
(a) merge line; (b) discontinuous line; (c) continuous line

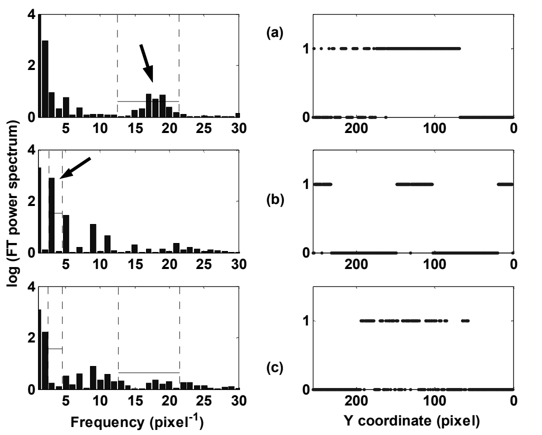
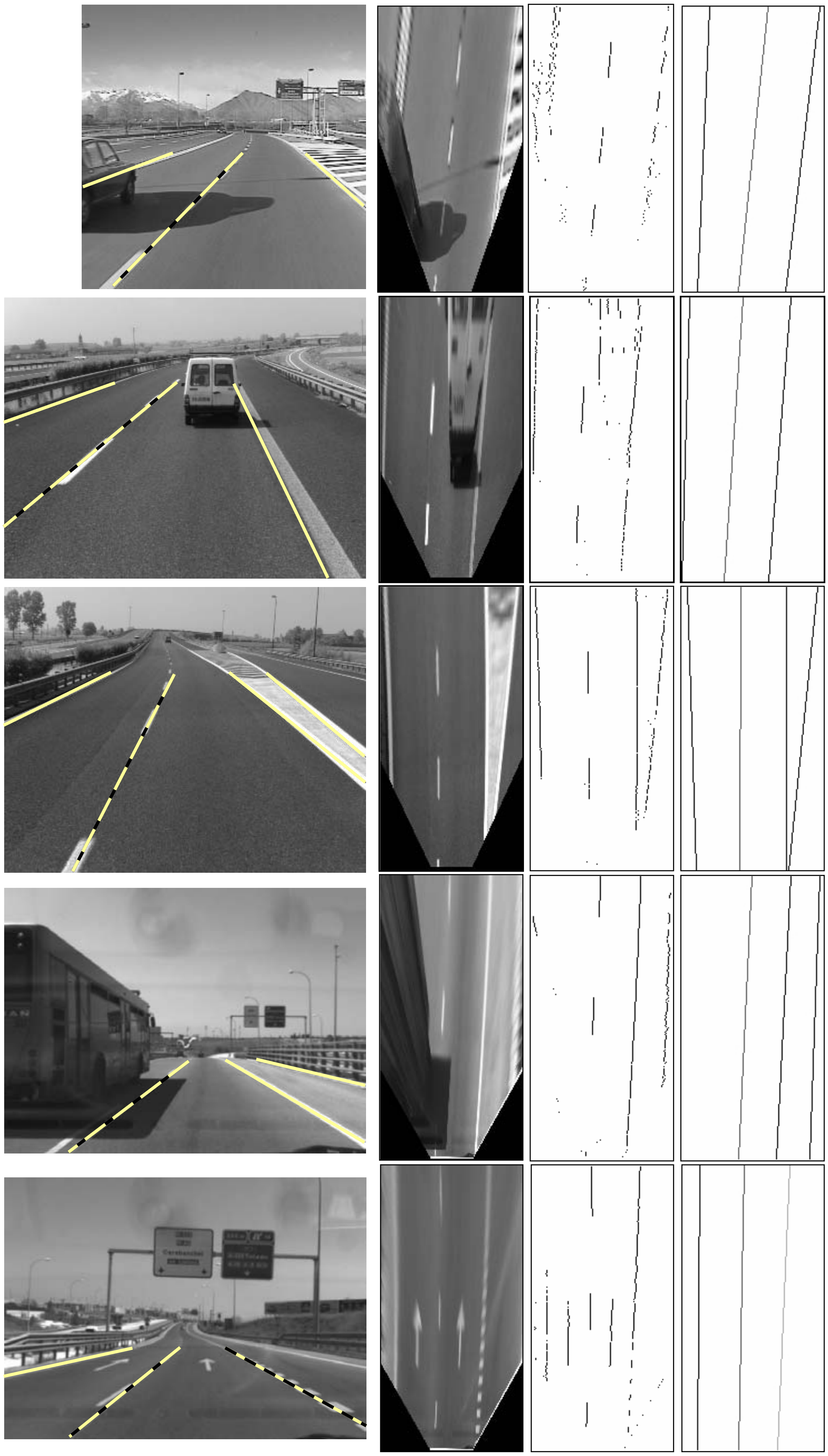


Fig. 6: Fourier analysis for the line profile extracted from the mark candidates image (Fig. 4-a). (a) merge line; (b) discontinuous line; (c) continuous line



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

Fig. 7 Examples of road lines detection (a) original image with detected lines; (b) remmaped; (c) thresholded; (d) lines detected, where black means continuous line.

Fig. 8 Classified lines superimposed to the original image. Red means "continuous", green "discontinuous", and blue "merge".

IV. Conclusions and Perspectives

In this article, the Lane Interpretation module of the Advanced Driver Assistance System for the IvvI project, has been presented. It is able to detect and classify the marked lines present in the image.

The algorithm works nearly in real time, and has been tested with some off-road video sequences. The line detection is robust to shadows and partial occlusions, as showed in Fig. 7. The lines of the own lane are rarely lost, even though the temporal integration is not yet implemented. The main problem, so far, is the presence of occasional false detections, especially when another vehicle is so close to the ego-vehicle that it occupies about 2/3 of the image. This problem will be overcome with the interaction between the Lane Interpretation and the Vehicle Detection module, so that the regions of the image which contains a vehicle will be excluded from the analysis. The road line classification works surprisingly good, and misclassifications are extremely rare.

Temporal integration will be implemented in the short term. Tracking of the road lanes will be accomplished with the CONDENSATION algorithm [11], which has several advantages over the Kalman filter. The use of a statistical approach for temporal integration implies the use of a top-down technique. Therefore, a model with a fixed number of lanes has to be fixed before fitting it to the image. This is not a problem, since the different types of road lines are recognized. The algorithm starts fitting a model with just one lane, and when a dashed line is detected, it continues searching for adjacent lanes until no detection is present, or a continuous line is encountered.

Acknowledgment

Authors thank the Instituto Elettrotecnico Nazionale Galileo Ferraris (IEN) for their road image sequences.

References

[1] J. M. Collado, C. Hilario, a. de la Escalera, and J. M. Armingol, "Model based vehicle detection for intelligent vehicles", *IEEE Intelligent Vehicles Symposium, Parma, Italy,* pp. 572-577, June 2004.

[2] A. Broggi, M. Bertozzi, A. Fascioli and G. Conte, *Automatic Vehicle Guidance: The Experience of the ARGO Autonomous Vehicle*, World Scientific, 1999

[3] D. A. Pomerleau and T. Jochem, "Rapidly adapting machine vision for automated vehicle steering", *IEEE Machine Vision*, pp. 19-27, April 1996.

[4] L. Vlacic, M. Parent and F. Harashima, *Intelligent Vehicle Technologies: Theory And Applications*, Butterworth-Heinemann, 2001.

[5] E. D. Dickmanns and B. D. Mysliwetz "Recursive 3-D road and relative ego-state recognition", *IEEE Transactions on Pattern Analysis and Machine Intelligence*, vol. 14, no. 2, pp. 199-213, February 1992.

[6] D. DeMenthon, "A zero-bank algorithm for inverse perspective of a road from a single image", *Proceedings IEEE International Conference on Robotics and Automation*, Raleigh, NC, pp. 1444-1449, April 1987

[7] K. Kanatani and K. Watanabe, "Reconstruction of 3-D Road Geometry from Images for Autonomous Land Vehicles", *IEEE Transactions on Robotics and Automation*, vol. 6, no. 1, February 1990.

[8] K. Kluge and S. Lakshmanan, "A deformable-template approach to lane detection", *Proceedings of the Intelligent Vehicles '95 Symposium*, pp. 54-59, September 1995.

[9] C. Kreucher and S. Lakshmanan, "LANA: a lane extraction algorithm that uses frequency domain features", *IEEE Transactions on Robotics and Automation*, vol. 15, no. 2, pp.343-350, April 1999.

[10] B. Southall, and C. J. Taylor, "Stochastic road shape estimation", *Computer Vision, 2001. ICCV 2001. Proceedings. Eighth IEEE International Conference on*; vol. 1, July 2001, pp. 205-212

[11] M. Isard and A. Blake, "CONDENSATION—Conditional density propagation for visual tracking", *International Journal of Computer Vision* 29(1), 5-28 (1998). Kluwer Academic Publishers, 1998.

[12] R. Chapuis, R. Aufrere and F. Chausse, "Accurate road following and reconstruction by computer vision", *IEEE Transactions on Intelligent Transportation Systems*, vol. 3, no. 4, December 2002.

[13] Y. Wang, D. Shen and E. K. Teoh, "Lane detection using spline model", *Pattern Recognition Letters*, vol.21, no.8, pp. 677-689, July 2000.

[14] A. L. Yuille and J. M. Coughlan, "Fundamental limits of Bayesian inference: order parameters and phase transitions for road tracking". IEEE *Transactions on Pattern Analysis and Machine Intelligence*, vol. 22, no. 2, pp. 160-173. Feb. 2000

[15] N. W. Campbell and B. T. Thomas, "Navigation of an autonomous road vehicle using lane boundary markings", *1st IFAC Int. Conference on Intelligent Autonomous Vehicles*, ed. D. Charnley, pp. 169-174, Pergamon Press, 1993.

[16] R. Risack, P. Klausmann, W. Küger and W.Enkelmann, "Robust lane recognition embedded in a real-time driver assistance system", *1998 IEEE International conference on Intelligent Vehicles*, pp. 35-40, 1998.

[17] R. Aufrére, R. Chapuis and F. Chausse, "A model-driven approach for real-time road recognition", *Machine Vision and Applications*, no. 13, pp. 95-107, May 2001.

[18] A. Broggi, "Robust real-time lane and road detection in critical shadow conditions", *Proceedings IEEE International Symposium on Computer Vision*, Coral Gables, Florida, pp. 353-358 November 1995.

[19] J. M. Collado, "Autocalibración de un sistema de visión estéreo para vehículos inteligentes mediante algoritmos genéticos", unpublished.

[20] P. L. Palmer, M. Petrou and J. Kittler, "A Hough Transform Algorithm with a 2D Hypothesis testing Kernel", *CVGIP: Image Understanding*, vol. 58, no. 2, pp. 221-234, September 1993.

[21] P. L. Palmer, J. Kittler and M. Petrou, "An Optimizing Line Finder Using a Hough Transform Algorithm", *Computer Vision and Image Understanding*, vol. 68, nº 1, pp. 1-23, July 1993.