A lane departure warning system using lateral offset with uncalibrated camera

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A Lane Departure Warning System Using Lateral Offset with Uncalibrated Camera

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***Abstract*— In this paper, we propose an automatic method for determining the lateral offset of the vehicle with respect to the center of the lane. Initially, a linear-parabolic model is used to detect lane boundaries. The linear part of the model is then used to obtain an estimation of the lateral offset, without the knowledge of any intrinsic or extrinsic camera parameter. Finally, the analysis the offset across time is then used to determine a lane departure measure, allowing lane crossings to be detected in advance.**

I. Introduction

Nowadays, an important social and economic problem is traffic safety. In 1999, about 800,000 people died globally in road related accidents, causing losses of around US$ 518 billion [1]. According to the United Nations [2], 1.26 million people died globally in road related accidents in 2000, leading to an average toll of 3,000 fatalities a day. A considerable fraction of these accidents is due to driver fatigue and/or inattention. In many cases, the driver falls asleep (mostly bus and truck drivers), making the vehicle to leave its designated lane and possibly causing and accident.

It is expected that machine vision systems can be used to improve safety on the roads, decreasing the number of accidents. In such systems, a video camera (and/or other sensors) is installed in the interior of the vehicle, and the environment is sensed to provide useful information for the conductor (such as speed limit, traffic lights, obstacles, etc.).

Several lane departure warning systems have been proposed in the past years [3]–[10], relying on a variety of computer vision techniques. In this paper, we use the linear-parabolic lane boundary model described in [10], [11] to compute the lateral offset of the vehicle with respect to the center of the lane, without needing camera parameters. The lateral offset is then used to obtain a lane departure measure.

The remainder of this paper is organized as follows. In Section II, several lane departure warning systems are discussed. Section III gives a brief description of the linear-parabolic lane model, and Section IV presents the proposed model for lateral offset computation and lane departure identification. Experimental results are provided in Section V, and conclusions are drawn in Section VI.

II. Related Work

The first step to develop a lane departure warning system is a robust detection of lane boundaries. Several models for lane boundaries have been proposed in the literature, with a diversity of approaches. For example, Beucher and his colleagues [12] worked on road segmentation and obstacle detection based on watersheds. Other authors [13], [14] used inverse perspective mappings to obtain top-view images. Deformable road models have also been widely used for lane detection [15]–[19]. These techniques attempt to determine mathematical models to fit road boundaries. Apostoloff and Zelinsky [20] proposed a lane tracking system based on particle filtering and multiple cues. Sotelo and his colleagues [21] used parabolic models to approximate lane boundaries in color video sequences. Jung and Kelber [11] proposed a linear-parabolic model for lane boundaries, using a linear function in the near vision field and a quadratic function in the far field.

Based on some kind of lane boundary estimation, other authors have worked on lane departure warning systems. LeBlanc et. al [3] used computer vision to detect lane boundaries, compared them with a geometric model of the road, and then estimated a time for lane crossing (TLC). Risack et. al [17] used both vision and radar-like information to estimate TLC. Lee [5] 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. A modification of this technique [7] includes a boundary pixel extractor to improve its robustness. Kim and Oh [8] proposed a lane departure warning system based on fuzzy techniques, by combining lateral offset information with TLC. Chang and collaborators [22] addressed the problem of collision detection and lane departure through lane detection and fuzzy classifiers. Volkswagen researchers [9] used several sensors (radar, vision and laser) to detect lane shifts. Jung and Kelber [10] used a linear-parabolic model for lane boundaries, and computed a lane departure metric based on the orientation of both lanes.

In general, methods for lane departure detection may be classified in two main classes: in the first, world coordinates are needed to estimate the vehicle's position and/or TLC [3], [8], [17]. For that purpose, either camera calibration or other sensors are required. On the other hand, the second class of techniques rely solely on image coordinates [5], [7], [10], and do not provide accurate estimates of the vehicle's position in world coordinates. In this paper, we explore the linear-parabolic model for lane boundaries proposed in [10] to automatically calibrate the camera, and obtain a lane departure metric based on world coordinates. The linear-parabolic model is a good choice because it combines

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the robustness of the linear model with the flexibility of the parabolic model, and shows good detection results in the presence of noise, shadows and different illumination conditions.

III. Linear-Parabolic Model for Lane Boundaries

As noticed by Risack et. al [17], at near distances (6-30 meters) the lane can be approximated by a linear model for highways. For farther distances, curved portions of the road are more distinguishable, due to perspective effects. Thus, our model deals with near and far vision fields separately, as described next.

Let us consider a coordinate system matching image coordinates, and a threshold x_m that separates the near and far vision fields, as shown in Figure 1 (the choice for x_m depends on camera parameters, such as tilt angle, size and quality of the acquired images). The linear-parabolic model is a combination of a linear function in the near field, and a parabolic function in the far field, having continuous and smooth connections.

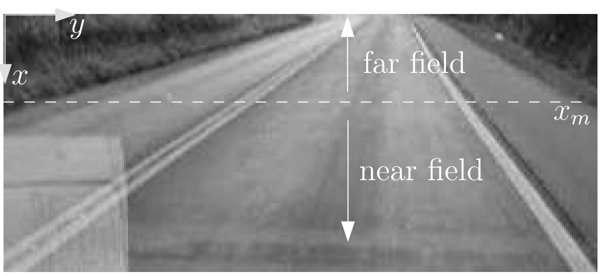

Fig. 1. One frame of a video sequence, with the coordinate system and delimitation of the near and far fields.

Mathematically, the lane boundary model $f(x)$ is given by:

$$f(x) = \begin{cases} a + bx, & \text{if } x > x_m \\ c + dx + ex^2, & \text{if } x \leq x_m \end{cases}, \tag{1}$$

where x_m represents the border between near and far fields. Although this model apparently presents 5 degrees of freedom, continuity and smoothness restraints imply that:

$$f(x) = \begin{cases} a + bx, & \text{if } x > x_m \\ \frac{2a + x_m(b-d)}{2} + dx + \frac{(b-d)}{2x_m}x^2, & \text{if } x \leq x_m \end{cases}. \tag{2}$$

Thus, Equation (2) indicates that our lane boundary model is characterized by only three coefficients (a, b and d). To determine these parameters, we use a weighted least squares method, fitting the proposed model to the images acquired by the camera.

Let us assume that both (right and left) lane boundaries were detected in the prior frame of the video sequence. In the current frame, it is expected that lane boundaries will be constrained to a neighborhood of the prior detection, called lane boundary region of interest (LBROI). Such LBROIs are "thick" curves obtained by dilating lane boundary models in the y direction, and will be the search space for boundaries in the current frame.

The edge image $|\nabla I(x, y)|$ of the current frame is computed within the LBROI. Although most of the edges will be related to the lane boundary, some edges related to noise, road texture or other structures will also appear. To remove these undesired edges, we apply an adaptive threshold based on the mean magnitude M_{mean} of the edges, and denote (x_{n_i}, y_{n_i}) the m coordinates of the non-zero pixels of the thresholded edge image belonging to the near field, and M_{n_i} the respective magnitudes ((x_{f_j}, y_{f_j}) and M_{f_j} represent the same characteristics for the n edge pixels in the far field).

To obtain the linear-parabolic lane model, we minimize the following weighted squared error:

$$E = \sum_{i=1}^{m} M_{n_i} \left[y_{n_i} - f(x_{n_i})\right]^2 + \sum_{j=1}^{n} M_{f_j} \left[y_{f_j} - f(x_{f_j})\right]^2, \tag{3}$$

by solving a 3×3 linear system. The LBROIs of the current frame are then used to compute the new linear-parabolic model in the subsequent frame, and so on. An example of the linear-parabolic model fitted to a curved portion of the road is illustrated in Figure 2. Locally (within the near field), the linear function is a good approximation, while the quadratic function fits well the curve in the far field. More details about the linear-parabolic model and the initial detection of lane boundaries can be found in [10], [11].

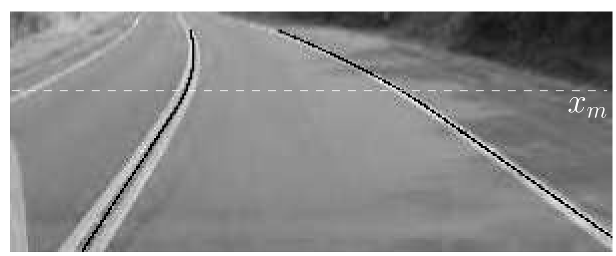

Fig. 2. Example of the linear-parabolic model fitted to a curved road.

IV. Lane Departure Detection Using Lateral Offset

A. Automatic Computation of Lateral Offset

Guiducci [23], [24] worked on road models and automatic camera calibration. He assumed that for high speed roads (radius of curvature typically larger than 1000 m) and for vehicle heading directions forming a small angle with the road direction (typically smaller than 5°), then lane borders can be modeled as hyperbolas on the image plane:

$$y - y_0 = A_i(x - x_0) + \frac{B}{x - x_0}, \quad \text{for} \quad i \in \{l, r\}, \tag{4}$$

where $i = l$ and $i = r$ correspond to the left and right lane boundaries, respectively. Also, (x_0, y_0) are the coordinates of the (common) vanishing point of the tangents to the road borders next to the vehicle, according to Figure 3.

The linear terms $y - y_0 = A_i(x - x_0)$ of Equation (4) are the image plane equations of the (slanting) asymptotes, that is, of the projection on the image plane of the tangents

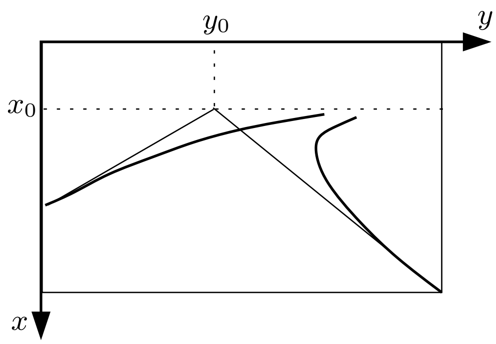

Fig. 3. Projection of a road in image coordinates.

to the left and right borders at the vehicle, while the term $B/(x - x_0)$ represents the deviation from straightness due to the horizontal curvature of the road (and is assumed to be the same for both borders). As noticed by Guiducci [24], the lateral offset of center of the vehicle with respect to the center of the lane can be computed through:

$$\frac{l_o}{W} = \frac{A}{\Delta A}, \tag{5}$$

where l_o is the lateral offset and W is the lane width, according to Figure 4. Also, parameters A and ΔA are given by:

$$A = \frac{A_l + A_r}{2} \quad \text{and} \quad \Delta A = A_l - A_r. \tag{6}$$

It should be noticed that the offset l_o does not depend on any intrinsic camera parameters (such as focal length), and can be automatically detected if the linear terms $y - y_0 = A_i(x - x_0)$ of Equation (4) are known. Also, the offset does not depend on the curvature-related parameter B. Since only a linear approximation of the near field is needed, we chose to use the linear part of the linear-parabolic lane model, due its simplicity and robustness. Hence, instead of fitting the hyperbolas suggested in [23], we compute the lateral offset l_o according to Equation (5), using the linear part of our lane boundary model.

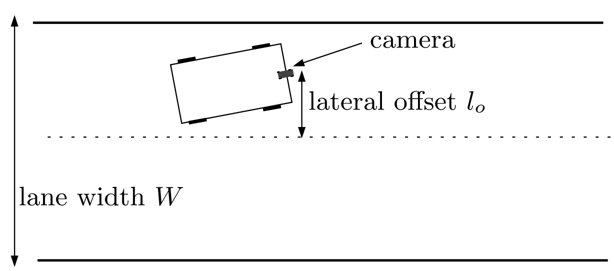

Fig. 4. Topview image of the travelling vehicle.

An example of the offset computation[1] using the linear-parabolic model is depicted in Figure 5. This Figure shows some frames of a video sequence, in which the vehicle starts travelling in the right lane and then shifts to the left lane.

[1]We assume that lane width W is unknown. Hence, when we refer to the lateral offset, we mean the relative offset l_o/W.

i	0	1	2	3	4
$w(i)$	0.2075	0.2062	0.2024	0.1962	0.1878

TABLE I

DISCRETE GAUSSIAN WEIGHTS USED TO FILTER RAW OFFSET VALUES l_o

It can be noticed that lane shift starts between frames 90 and 100, and the offset value increases. Close to frame 114, the central axis of the vehicle is crossing lane boundaries (because $l_o/W \approx 0.5$), and around frame 145 lane shift is completed (because $l_o/W \approx 1$, and keeps approximately constant). It can be observed that the linear-parabolic lane model correctly fits lane boundaries at frame 197, despite shadows cast by trees on the left side of the road. More results of the linear-parabolic model in video sequences containing shadows and/or weak lane painting can be found in [10], [11].

B. Lane Departure Detection

The lateral offset of the vehicle with respect to the center of the lane has been used to predict lane departure [17], [25]. However, existing techniques depend on some kind of camera calibration procedure to obtain the offset, while the proposed algorithm does not require any intrinsic or extrinsic camera parameters. In this work, we analyze both the lateral offset and its rate of growth at each frame, as explained next.

If the vehicle is travelling parallel to lane boundaries and exactly at the center of the lane, then the lateral offset $l_o(k)$ as a function of time will be constant and equal to zero[2]. If the vehicle is travelling parallel to lane boundaries, but displaced from the center of the lane, $l_o(k)$ will still be constant, but with a non-zero value (in fact, this value can be close to ± 0.5, if the vehicle is close to one lane boundary). In this case, no lane departure warning signal should be fired, because the vehicle does not appear to be leaving its lane. Thus, analyzing only the value of $l_o(k)$ is not sufficient to detect tendencies of lane departure. In fact, it is also important to analyze its behavior across several frames, by computing its rate of change.

Computed offset values $l_o(k)$ are usually noisy, due to irregularities in the pavement, or bad condition of road painting. In particular, these disturbances propagate when computing finite differences. To remove such high-frequency variations in the signal $l_o(k)$, we apply a causal temporal filter in five consecutive frames (which corresponds to approximately 0.33 seconds for videos captured at 15 FPS):

$$l_o^{\text{filt}}(k) = \sum_{i=0}^{4} w(i) l_o(k - i), \tag{7}$$

where $w(i)$ are Gaussian weights based on the left-half of the Normal distribution, normalized so that $\sum w(i) = 1$. Such weights are provided in Table I. It should be noticed that a relatively large standard deviation was used, to provide more denoising power to the filtering process.

[2]Here, $l_o(k)$ denotes the lateral offset at the $k-th$ frame of the video sequence.

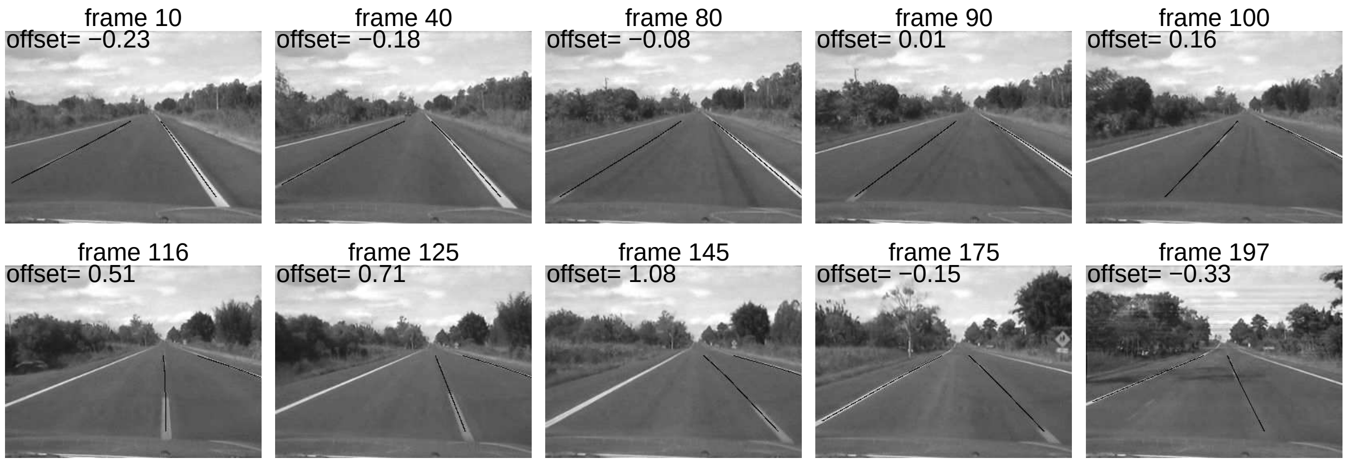

Fig. 5. Frames of video sequence 1 and corresponding lateral offsets.

The rate of change of the lateral offset given by 1st order finite differences:

$$dl_o(k) = l_o^{\text{filt}}(k) - l_o^{\text{filt}}(k-1). \tag{8}$$

For lane departure detection, we must check if the vehicle is relatively far from the center of the lane, and if this distance is increasing or decreasing (i.e., if the heading direction of the vehicle is pointing towards the center of the lane or away from it in a certain time interval). A lane departure warning signal is issued at frame k if one of the following conditions are satisfied:

$$l_o(k) > T_c \text{ and } dl_o(j) > 0, \text{ for } k - N < j \leq k \text{ or} \tag{9}$$

$$l_o(k) < -T_c \text{ and } dl_o(j) < 0, \text{ for } k - N < j \leq k, \tag{10}$$

where T_c is the minimum distance from the center of the lane, and N is the number of consecutive frames that are analyzed. For all experiments, we used $T_c = 0.25$ (corresponding to a quarter of the lane width), and $N = 5$ (corresponding to a time interval of approximately 0.33 seconds). Conditions (9) and (10) correspond to lane departures to the left and to the right, respectively.

When a lane departure is detected and the offset value keeps approximately constant for a number of frames (e.g. 10 frames), a complete lane shift is identified. In such cases, the systems reinitializes, meaning that the left lane boundary becomes the right lane boundary, and the left boundary is recomputed using the procedure described in [11] (when a right-to-left shift is detected). An analogous procedure is applied in left-to-right shifts.

V. Experimental Results

Our preliminary results indicate that the proposed lane departure identification system can effectively predict lane crossings. For example, let us consider the video sequence related to Figure 5. In this sequence, the vehicle starts on the right lane, shifts to the left and returns to its original lane. It keeps its lane for a while, and repeats the same movements. Figure 6 illustrates the offset values for the first 1000 frames of the sequence. It also shows that lane departure warnings were issued at frames 104, 190, 679 and 766 (regions related to warnings are marked with patches). Discontinuities at frames 170, 260, 731 and 838 correspond to complete lane shifts (when lane boundaries are re-computed).

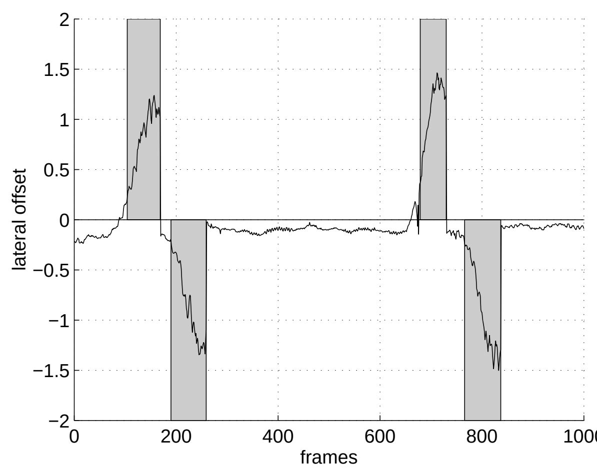

Fig. 6. Offset values and lane departure detection (patched regions) for video sequence 1.

In another experiment, we filmed a road with three lanes. The vehicle starts it trajectory on the right lane, changes to the central lane, shifts to the left lane, returns to the central lane and then to the right lane again. Figure 7 illustrates the offset values for the first 1150 frames of the sequence, and the sets of frames when lane departure warnings were issued (filled patches). Lane departure warning signals were fired at frames 75, 328, 576 and 689. In Figure 8, some frames of video sequence 2 are illustrated. It can be noticed that lane departure warning signals were correctly issued, several frames before lane crossing was completed.

The proposed lane departure system may not work if other vehicles are travelling closely in front of the camera. In such cases, lane markings could be occluded, and our lane detection algorithm would probably fail.

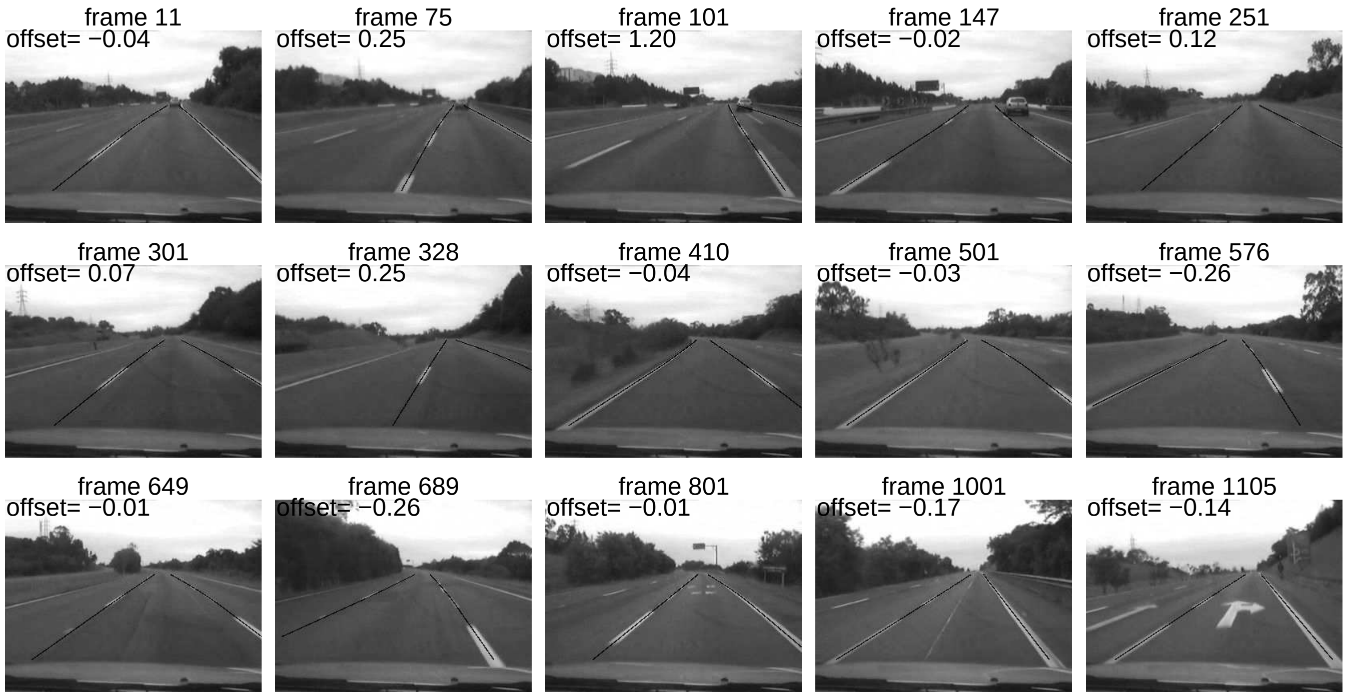

Fig. 8. Frames of video sequence 2 and corresponding lateral offsets.

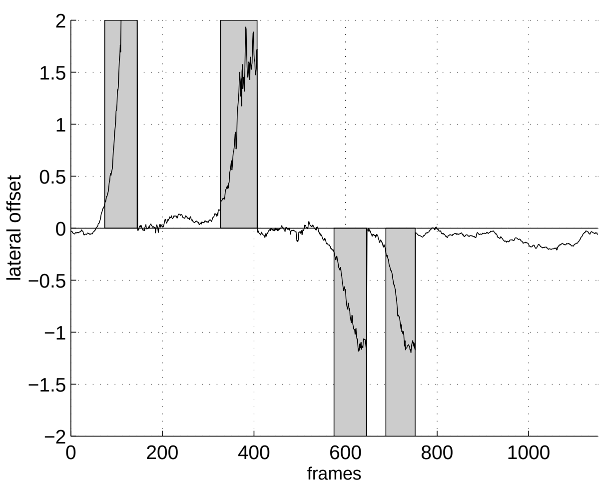

Fig. 7. Offset values and lane departure detection (patched regions) for video sequence 2.

VI. Concluding Remarks

In this paper, we proposed a new lane departure warning system based on the lateral offset of the vehicle with respect to the center of the lane. Initially, a linear-parabolic model is used to detect lane boundaries, and the linear part (corresponding to the near vision field) is used to compute the lateral offset without needing information about camera parameters. Such offset is analyzed across time, and a lane departure warning signal is issued when the vehicle approaches lane boundaries.

Our preliminary results indicate that the proposed technique correctly predicts in advance tendencies of lane departure for video sequences obtained in different environmental conditions (presence of shadows, weak lane paintings, varying illumination, etc.).

Future work will concentrate on studying the use of Kalman filters to obtain more accurate estimates of the lateral offset, and using the lateral offset for autonomous navigation.

VII. Acknowledgment

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References

[1] G. Jacobs, A. Aeron-Thomas, and A. Astrop, “Estimating global road fatalities,” Australian National University, Transport Research Laboratory, Technical Report TRL 445, 1999.

[2] J. Hagen., “Road safety crisis,” *UN Chronicle Online Edition.*, 2004, http://www.un.org/Pubs/chronicle/2004/webArticles/012204_road_safety.asp.

[3] D. J. LeBlanc, P. J. V. G. E. Johnson, G. Gerber, R. D. Sonia, R. D. Ervin, C.-F. Lin, A. G. Ulsoy, and T. E. Pilutti, “CAPC: A road-departure prevention system,” *IEEE Control Systems Magazine*, vol. 16, pp. 61–71, December 1996.

[4] U. Hofmann, A. Rieder, and E. D. Dickmanns, “EMS-vision: Application to hybrid adaptive cruise control,” in *Proceedings of IEEE Intelligent Vehicles Symposium*, 2000, pp. 468–473.

[5] J. W. Lee, “A machine vision system for lane-departure detection,” *Computer Vision and Image Understanding*, vol. 86, no. 1, pp. 52–78, April 2002.

[6] V. Kastrinaki, M. Zervakis, and K. Kalaitzakis, “A survey of video processing techniques for traffic applications,” *Image and Vision Computing*, vol. 21, no. 4, pp. 359–381, April 2003.

[7] J. W. Lee, C.-D. Kee, and U. K. Yi, “A new approach for lane departure identification,” in *Proceedings of IEEE Intelligent Vehicles Symposium*, Columbus, OH, June 2003, pp. 100–105.

[8] S.-Y.Kim and S.-Y. Oh, “A driver adaptive lane departure warning system based on image processing and a fuzzy evolutionary technique,” in *Proceedings of IEEE Intelligent Vehicles Symposium*, Columbus, OH, June 2003, pp. 361–365.
[9] K. Weiss, N. Kaempchen, and A. Kirchner, “Multiple-model tracking for the detection of lane change maneuvers,” in *Proceedings of IEEE Intelligent Vehicles Symposium*, Parma, Italy, 2004, pp. 937–942.
[10] C. R. Jung and C. R. Kelber, “A lane departure warning system based on a linear-parabolic lane model,” in *Proceedings of IEEE Intelligent Vehicles Symposium*, Parma, Italy, 2004, pp. 891–895.
[11] ——, “A robust linear-parabolic model for lane following,” in *Proceedings of SIBGRAPI*, Curitiba, PR, October 2004, pp. 72–79.
[12] S. Beucher and M. Bilodeau, “Road segmentation and obstacle detection by a fast watershed transformation,” in *Proceedings of IEEE Intelligent Vehicles Symposium*, October 1994, pp. 296–301.
[13] M. Bertozzi and A. Broggi, “Real-time lane and obstacle detection on the gold system,” in *Proceedings of IEEE Intelligent Vehicles Symposium*, 1996, pp. 213–218.
[14] ——, “GOLD: A parallel real-time stereo vision system for generic obstacle and lane detection,” *IEEE Transactions on Image Processing*, vol. 7, no. 1, pp. 62–81, 1998.
[15] Y. Wang, D. Shen, and E. Teoh, “Lane detection using catmull-rom spline,” in *Proceedings of IEEE Intelligent Vehicles Symposium*, Stuttgart, Germany, 1998, pp. 51–57.
[16] J. Goldbeck and B. Huertgen, “Lane detection and tracking by video sensors,” in *Proceedings of IEEE Intelligent Transportation Systems*, vol. 1, October 1999, pp. 74–79.
[17] R. Risack, N. Mohler, and W. Enkelmann, “A video-based lane keeping assistant,” in *Proceedings of IEEE Intelligent Vehicles Symposium*, Dearborn, MI, October 2000, pp. 506–511.
[18] J. Park, J. Lee, and K. Jhang, “A lane-curve detection based on an LCF,” *Pattern Recognition Letters*, vol. 24, no. 14, pp. 2301–2313, October 2003.
[19] Y. Wang, E. Teoh, and D. Shen, “Lane detection and tracking using B-snake,” *Image and Vision Computing*, vol. 22, no. 4, pp. 269–280, April 2004.
[20] N. Apostoloff and A. Zelinsky, “Robust based lane tracking using multiple cues and particle filtering,” in *Proceedings of IEEE Intelligent Vehicles Symposium*, Columbus, OH, June 2003, pp. 558–563.
[21] M. A. Sotelo, F. J. Rodríguez, L. Magdalena, L. M. Bergasa, and L. Boquete, “A color vision-based lane tracking system for autonomous driving on unmarked roads,” *Autonomous Robots*, vol. 16, no. 1, pp. 95–116, October 2004.
[22] T.-H. Chang, C.-H. Lin, C.-S.Hsu, and Y.-J. Wu, “A vision-based vehicle behavior monitoring and warning system,” in *Proceedings of IEEE Intelligent Transportation Systems*, vol. 1, October 2003, pp. 448–453.
[23] A. Guiducci, “Parametric model of the perspective projection of a road with applications to lane keeping and 3d road reconstruction,” *Computer Vision and Image Understanding*, vol. 73, no. 3, pp. 414–427, March 1999.
[24] ——, “Camera calibration for road applications,” *Computer Vision and Image Understanding*, vol. 79, no. 2, pp. 250–266, August 2000.
[25] S. Lee, W. Kwon, and J.-W. Lee, “A vision based lane departure warning system,” in *Proceedings of IEEE International Conference on Intelligent Robots and Systems*, 1999, pp. 160–165.