A Driver Warning System Based on the LOIS Lane Detection Algorithm

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Abstract - **Recent investigations into intelligent lane tracking have yielded several systems that can find lane locations in still images with high efficacy. More recently, the LOIS (Likelihood of Image Shape) algorithm has been shown to robustly find lane markers even in the presence of shadowing, occlusion, and varied lighting conditions. This paper uses the LOIS algorithm in order to track the lanes through a sequence of images, and provide a warning if a lane crossing is imminent.**

Specifically, the vehicle's offset with respect to the right and left lane markings (as determined by LOIS) are examined as a function of time. A Kalman filter is used to predict the future values of these offset parameters, based on past observations. If the vehicle's position as determined LOIS is within one meter of either the left or the right lane marking, and if the vehicle's path as predicted by the Kalman filter will lead to it being within 0.8 meters of either lane markings in less than one second, then a lane crossing warning is generated.

I. Introduction

Over the last decade a great deal of research has been performed in the area of vision-based detection of lane boundaries. This technology has a number of potential applications. One high-value potential application is drowsy driver warning. There are over three million traffic accidents each year in the U.S. in which a vehicle leaves the roadway without colliding with another vehicle. These accidents result in 13,000 deaths annually, and are responsible for 16.5% of all traffic delays. It is estimated that up to 53% of these accidents could be avoided if vehicles had lane departure warning systems [1]. Another potential application is to enhance the accuracy of tracking the leading vehicle for intelligent cruise control. Loss of correct tracking when the leading vehicle enters a curve is a significant cause of problems for ICC systems, and methods for detecting curves based on estimates of the motion of either the leading vehicle or one's own vehicle have limitations [2]. A longer-term application is to provide autonomous lateral vehicle control [3]. Vision-based techniques for autonomous lateral control have the advantage of using existing visual cues in the road environment, compared to infrastructure-based methods that require modification of the road.

A distinction can be made between the problems of lane detection and lane tracking. Lane detection involves determining the location of the lane boundaries in a single image without strong prior knowledge regarding the lane position. Lane tracking involves determining the location of the lane boundaries in a sequence of consecutive images, using information about the lane location in previous images in the sequence to constrain the probable lane location in the current image. Some systems use different algorithms for lane detection and tracking. The VaMoRs system, for instance, uses the algorithm described in [4] to perform the initial detection of the road, then switches to the algorithm described in [5] to perform frame-to-frame tracking of the lane location. The approach taken in the work described in this paper is to use the same basic image processing for lane detection and tracking, the LOIS Lane Detector.

LOIS (for *Likelihood Of Image Shape*) uses a deformable template approach. A parametric family of shapes describes the set of all possible ways that the lane edges could appear in the image. A function is defined whose value is proportional to how well a particular set of lane shape parameters matches the pixel data in a specified image. Lane detection is performed by finding the lane shape parameters that maximize the function for the current image.

The LOIS algorithm is used to track lanes from frame-to-frame. LOIS uses a weaker prior model of lane location when performing initial lane detection, then uses information from the previous frame to constrain the probable lane location when performing lane tracking. LOIS' output includes the curvature, orientation, and offsets of the current lane. The lane offsets are used in conjunction with a Kalman filter to predict the position of the vehicle, with respect to the lanes, in future frames. If a lane crossing is deemed imminent within one second, then a warning is generated. Several experimental results are presented in this paper to illustrate the effectiveness of this warning strategy.

Previous articles on LOIS [6][7][8] have focused on locating the lane boundaries in single images in situations where the vehicle remained near the center of the lane. A more recent work [9] deals with tracking the lane boundaries through sequences of images, including sequences where the vehicle performs maneuvers such as lane changes and excursions which take it far away from the lane center. This paper focuses on using the LOIS lane tracker to estimate the imminent lane crossings.

The rest of the paper is organized as follows. In section II, we present a brief review of some related work, followed by a description of LOIS in section III. Section IV contains details on lane tracking using LOIS. The strategy for warning drivers about imminent lane crossing is described in section V along with supporting experimental results. The paper concludes with a discussion of some relevant issues in section VI.

II. RELATED WORK

The first-generation of lane detection systems were all edge-based. They relied on thresholding the image intensity to detect potential lane edges, followed by a perceptual grouping of the edge points to detect the lane markers of interest. Also, often times the lanes to be detected were assumed to be straight. See [10][11][12] and the references therein. The problem with thresholding the intensity is that, in many road scenes, it isn't possible to select a threshold which eliminates the detection of noise edges without also eliminating the detection of true lane edge points. Therefore, these first generation lane detection systems suffered when the images contained extraneous edges due to vehicles, on-off ramps, puddles, cracks, shadows, oil stains, and other imperfections in the road surface. The same deficiency also applied when the lanes were of low contrast, broken, occluded, or totally absent.[1]

The second-generation of systems sought to overcome this problem by directly working with the image intensity array, as opposed to separately detected edge points, and using a global model of lane shape. For example, ARCADE [12] uses global road shape constraints derived from an explicit model of how the features defining a road appear in the image plane. A simple one-dimensional edge detection is followed by a least median squares technique for determining the curvature and orientation of the road. Individual lane markers are then directly determined by a segmentation of the row-averaged image intensity values. ARCADE, unlike its predecessors, does not require any perceptual grouping of the extracted edge points into individual lane edges. The RALPH system [3] is another example of a second generation lane detection system. Like ARCADE, it too uses global road shape constraints. The crux of RALPH is a matching technique that adaptively adjusts and aligns a template to the averaged scanline intensity profile in order to determine the lane's curvature and lateral offsets. There are several other such second generation systems; the reader is referred to [13] for a description of those. Many of these have been subject to several hours of testing, which involved the processing of extremely large and varied data sets, and it suffices to say that the second generation lane detection systems perform significantly better in comparison to the first generation ones.

The success and reliability of such second-generation lane detection/tracking systems has prompted several researchers to implement vision-based lane departure warning and lateral control systems. Foremost among these is RALPH [3], which was described in the previous paragraph. AURORA [1] uses a side-looking camera to determine the vehicle's offset from the lane, and generate a warning if a lane crossing is imminent within a second and a half. The estimate of time-to-lane-crossing (TLC) is based on a linear extrapolation of the current and half-second prior values of the offset. The CAPC system [16] uses a single forward-looking camera along with vehicle motion and steering angle sensors to predict imminent lane departures. A Kalman filter is used to predict the vehicle's future path, based on past observations. Another such system is described in [17]. Of course, the effectiveness and reliability of these warning/control systems are contingent on the performance of the underlying lane detection algorithms.

[1] As would be the case when the road has no lane markers, but only pavement edges.

III. THE LOIS ALGORITHM

The deformable template approach to object detection has three components:

- A parametric family of shapes which describes all possible ways that the object can appear in the image;
- A likelihood function which measures how well a particular hypothesized object shape matches a given image; and
- A method for finding the shape parameters that maximizes the likelihood function for the image being examined.

Each of these components is described in detail below.

A. *Prior Model of Lane Shapes*

Assume that the lane edges are circular arcs on a flat ground plane. For small to moderate curvatures, a circular arc with curvature *k* can be closely approximated by a parabola of the form

$$x = 0.5 * k * y^2 + m * y + b \qquad (1)$$

The derivation of the class of corresponding curves in the image plane is given for the case of an untilted camera, but it can be shown that the same family of curves results when the camera is tilted. Assuming perspective projection, a pixel *(r, c)* in the image plane projects onto the point *(x, y)* on the ground plane according to the equations

$$x = c * cf * y, \text{ and} \qquad (2)$$

$$y = \frac{H}{r * rf} \qquad (3)$$

where *H* is the camera height, *rf* is the height of a pixel on the focal plane divided by the focal length, and *cf* is the width of a pixel on the focal plane divided by the focal length. Substituting (2) and (3) into (1) and performing some simple algebraic manipulation results in the image plane curve

$$c = \frac{0.5 * k * H}{rf * cf * r} + \frac{b * rf * r}{H * cf} + \frac{m}{cf} \qquad (4)$$

or, combining the ground plane and camera calibration parameters together,

$$c = k' / r + b' * r + vp \qquad (5)$$

In the case of a tilted camera, the same family of curves results if the image coordinate system is defined so that row 0 is the horizon row. For left and right lane edges defined by concentric arcs the approximation is made that the arcs have equal curvature and equal tangential orientation where they intersect the X axis, so k' and vp will be equal for the left and right lane edges. As a result, the lane shape in an image can be defined by the four parameters $k', b'_{LEFT}, b'_{RIGHT}$, and vp.

B. The likelihood function

The intuition underlying the likelihood function used by LOIS is that there should be a brightness gradient near every point along the lane edges. The larger the magnitude of that gradient, the more likely it is to correspond to a lane edge. Also, the closer the orientation of that gradient is to perpendicular to the lane edge, the more likely it is to correspond to a lane edge. This likelihood function operates on raw image gradient information without the need for explicit thresholding to select edge points. As a result, weak edges with consistent gradient orientations can support the correct lane shape hypothesis, while strong edges with inconsistent orientations (such as those resulting from shadows) do not distract LOIS from finding the correct lane shape.

More formally, define the penalty function

$$f(a, x) = 1/(1 + a * x^2) \tag{6}$$

where a determines how fast $f(a, x)$ decreases as x increases. Then the contribution of each pixel to the likelihood value is equal to

$$GradMag_{pixel} * f(a_1, Dist_{pixel}) * f(a_2, \cos(GradOrient_{pixel} - LaneEdgeTgt) \tag{7}$$

where, $Dist_{pixel}$ is the distance in columns from the closest lane edge (left or right), and $LaneEdgeTgt$ is the tangential orientation of the closest lane edge calculated for the pixel's row. The calculation of the likelihood function clips the portions of the image more than a specified distance from the hypothesized lane edges in order to increase the speed of the function. Also, lookup tables are used for *cos(x)* and the penalty function *f(x)* in order to further increase the speed of the likelihood function calculation.

C. MAP Estimation and the Metropolis Algorithm

The prior and likelihood models are combined in a Bayesian framework, resulting in the lane detection problem being posed as finding the *Maximum A Posteriori* estimate of the lane shape parameters,

$$\begin{aligned}(k^*, b^*_{LEFT}, b^*_{RIGHT}, vp^*) &= \underset{k', b'_{LEFT}, b'_{RIGHT}, vp}{\operatorname{argmax}} \; P(k', b'_{LEFT}, b'_{RIGHT}, vp \mid \text{grad field}) \\ &= \underset{k', b'_{LEFT}, b'_{RIGHT}, vp}{\operatorname{argmax}} \; (\operatorname{atan}((b'_{RIGHT} - b'_{LEFT}) - 1) - \\ &\quad \operatorname{atan}((b'_{RIGHT} - b'_{LEFT}) - 3)) * L(k', b'_{LEFT}, b'_{RIGHT}, vp)\end{aligned} \tag{8}$$

In general, the function in eq. (8) is not a concave function, and often contains several local maxima. As a result, local optimization techniques such as gradient descent are not appropriate. The current implementation of LOIS uses the Metropolis algorithm with a geometric annealing schedule [15] to perform this maximization (see [6][7][8] for a more detailed description).

All the results shown in this paper were generated by running the Metropolis algorithm for 40 iterations. In each iteration a small step away from the current value is tested for each of the lane shape parameters. The initial temperature is 10.0, and the final temperature is 0.01.

D. Experimental Results Using LOIS

Figure 1 shows examples LOIS' lane detection ability under a variety of road and environmental conditions.

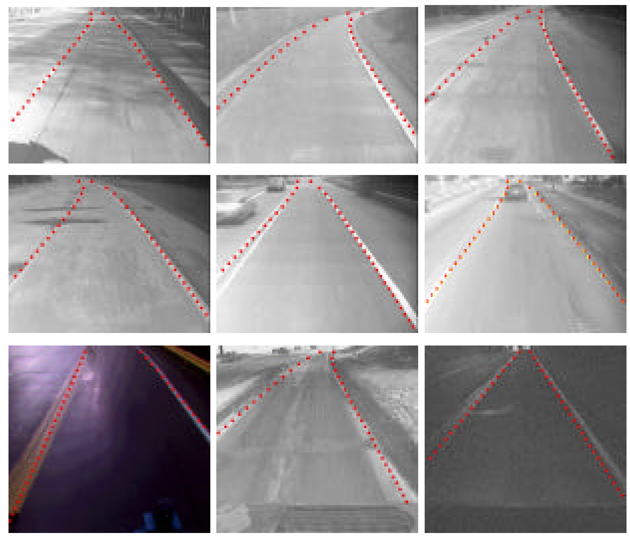

Figure 1. Examples of LOIS detecting lanes

LOIS has been tested on a very large number of images. Shown in Figure 2 are the cumulative results of the center of the lane as determined by LOIS. The data set used to generate this result consists of approximately 1,400 images acquired in sequence as an U.S. Army HMMWV was being driven for over 45 miles of regular Michigan highways (the route is also shown in Figure 2. The standard deviation in offset with respect to the center of the lane (a combination of errors due to both LOIS and the driver) was determined to be close to 13cms.

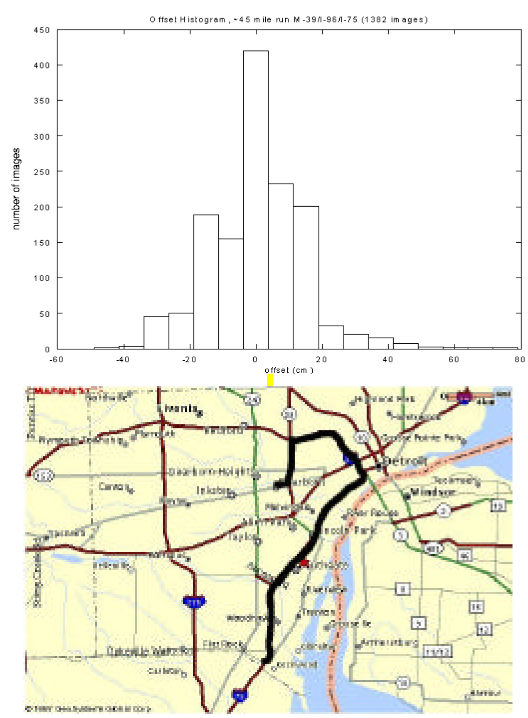

Figure 2. Lane detection using LOIS on a large data set

IV. LOIS-BASED LANE TRACKER

Clearly, roadway images taken in succession and spaced closely together (at a 10Hz rate, as for example in [14]) have very similar lane locations from frame to frame. This section describes how this temporal similarity can be exploited when looking for lanes in individual images.

The lane shape parameters $k', b'_{LEFT}, b'_{RIGHT}$, *and* vp of the previous frame are used as a starting point of the Metropolis algorithm for the succeeding image. Our specific implementation of the Metropolis algorithm, remembers the likelihood values corresponding to points that are in the "neighborhood" of the current lane shape parameters. So, if the previous lane shape parameters correspond to a point "near" the peak of the current likelihood, then using the previous values of $k', b'_{LEFT}, b'_{RIGHT}$, *and* vp as a starting point also results in a speed-up in the Metropolis algorithm's rate of convergence to the peak of the current likelihood. The sequence of images shown in Figure 3, represent a vehicle keeping within its lane. In each individual still image, the location of the lane in the previous frame has been used as a starting point for lane searches in the current frame. Such a strategy seems to achieve the intended purpose.

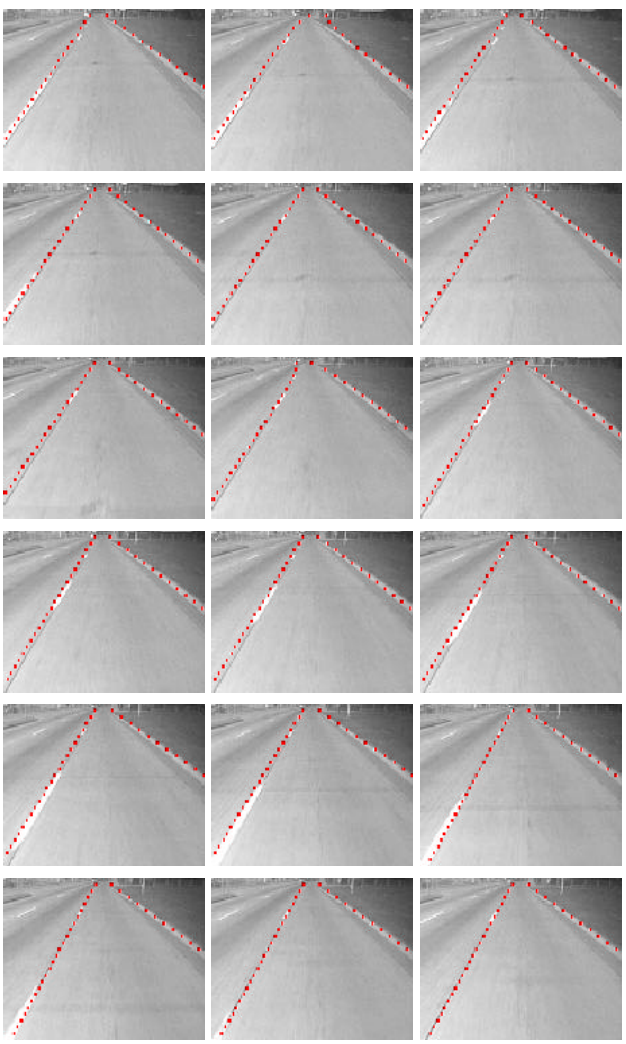

Figure 3. Lane tracking when there is no lane change

A common malady among most lane tracking systems is finding lanes during a sequence in which a vehicle is making a lane change, as it represents a situation where temporal correlation is detrimental. This problem is further compounded by the fact that the *a priori* contraints on lane shapes that are commonly used become invalid during this maneuver - e.g., that the right lane is to the right of the vehicle or that the left lane is within a certain distance of the vehicle. The LOIS-based lane tracking system overcomes this problem as shown in Figure 4 – see [9] for details.

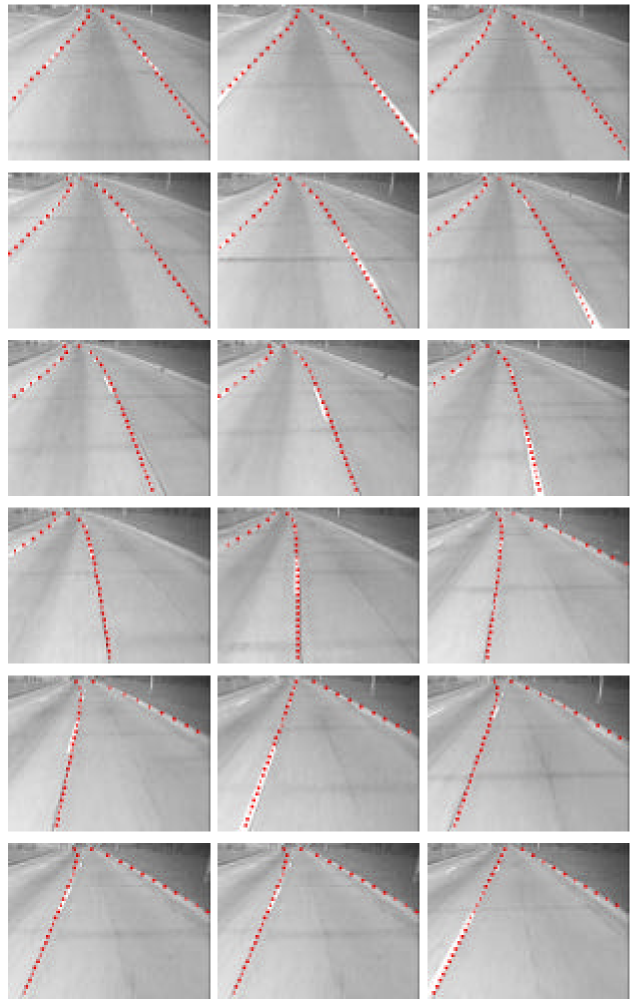

Figure 4. Lane tracking through a lane change maneuver

One danger of using past lane estimates to influence the current lane finding procedure is that bad estimates in the past may confine the current search to a poor solution space. Without proper consideration, the lane tracker could lose the lanes in one frame and never be able to recapture them in subsequent frames. This, however, is not a concern in the LOIS-based lane tracker, because the past lane shape estimate is used only as an initial guess of the current lane locations, without any additional constraints as shown in Figure 5 – again, see [9] for details.

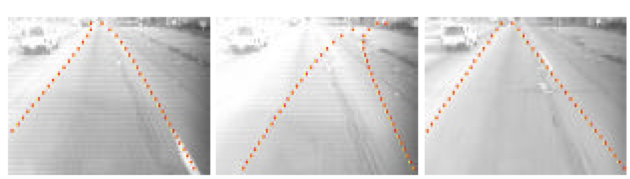

Figure 5. Recovering from a "bad" lane shape estimate

V. LANE DEPARTURE WARNING

The lane departure warning system described in this paper is based on a Kalman filtering acting on the left and right lane offset parameters output by LOIS. The filter derivation proceeds as follows:

Let $S_L(k) = \begin{bmatrix} S_{LEFT}(k) \\ S'_{LEFT}(k) \end{bmatrix}$ denote a state vector that contains the vehicle's true offset and lateral velocity with respect to the left lane on the image plane. The vehicle dynamics (in the absence of any other inertial and/or position information) is assumed be simple enough that

$$S_L(k+\Delta) = \begin{bmatrix} 1 & \Delta \\ 0 & 1 \end{bmatrix} S_L(k) + w(k) \text{, and}$$

$$b'_{LEFT}(k) = \begin{bmatrix} 1 & 0 \end{bmatrix} S_L(k) + v(k) \qquad (9)$$

are the state and observation equations for the offset of the vehicle with respect to the left lane. The parameter Δ in eq. (9) denotes the look-ahead time increment. Based on these state and observation equations, a linear minimum mean squared error (i.e., Kalman) estimate of $S_L(k+\Delta)$ based on all previous values of $b'_{LEFT}(k)$ is obtained. Similarly, for $S_R(k+\Delta)$.

If $S_{L,R}(k+\Delta)$ is less than a predetermined threshold and concurrently $b'_{LEFT,\,RIGHT}(k)$ is less than another predetermined threshold, a lane departure warning is generated.[2] Similarly for the right lane.

The resolution of the acquired image has a definite effect on the accuracy of this warning. At low image resolution, the quantization in the values of $b'_{LEFT}(k)$ and $b'_{RIGHT}(k)$ become very coarse. As a result, the Kalman filter based prediction of imminent lane departures becomes unreliable. To overcome this difficulty LOIS' b'_{LEFT} and b'_{RIGHT} outputs are averaged over a short window before using them in the Kalman filter.

The lane departure warning strategy adopted in this paper is susceptible to false alarms immediately following a gradual lane change maneuver. This is due to the fact that the vehicle remains very close to the lane for short periods upon crossing the lane. Such false alarms are eliminated by automatically turning the warning off immediately following lane change detection.

Figures 6 through 8 present examples of the lane departure warning system presented in this paper. In all of the figures, the warning is indicated by a small rectangle in the upper left or right corner of the image, depending on which lane the driver is nearing. Figure 6 shows the effectiveness of this warning during a lane change maneuver. Figure 7 shows the effectiveness of this warning during night time driving. Figure 8 shows the effectiveness of this warning during drowsy driving.

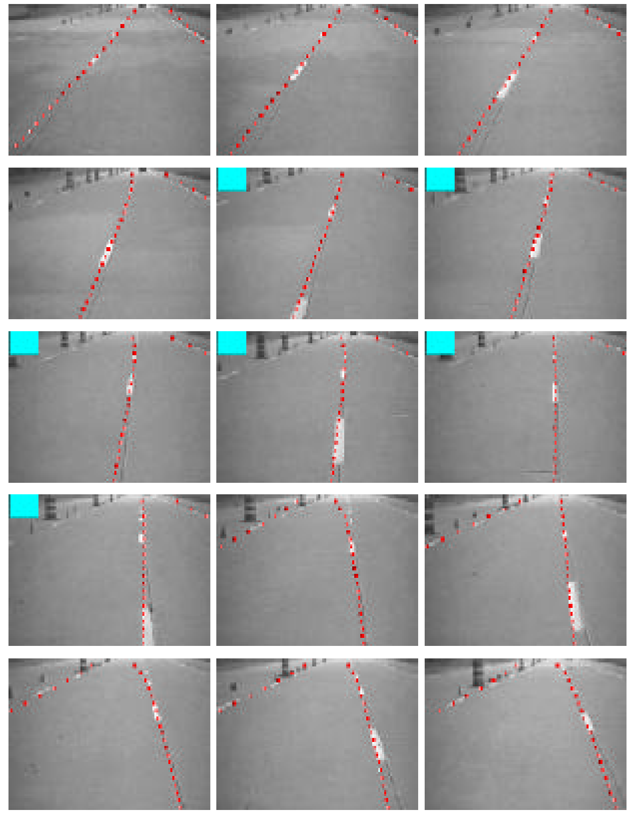

Figure 6. Departure warning during a lane change

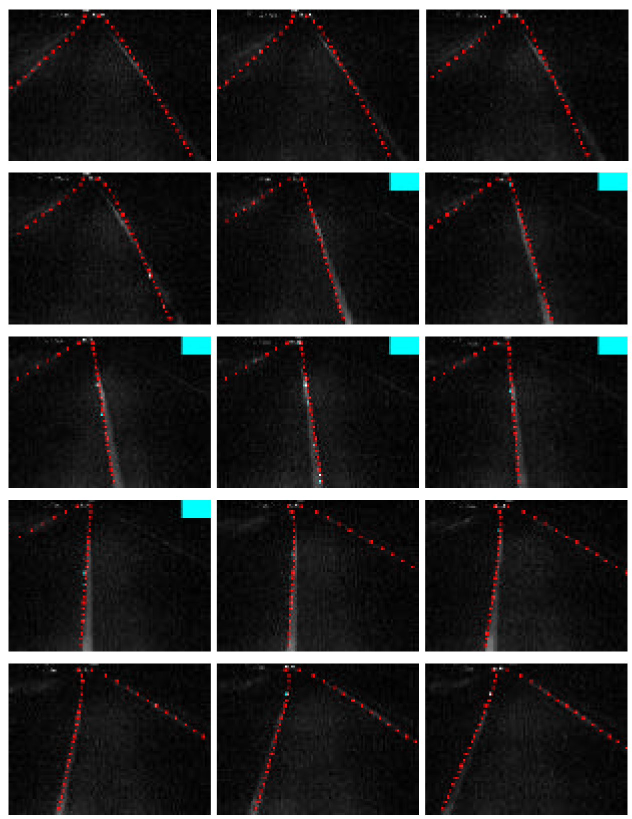

Figure 7. Departure warning at night time

[2] For the results in this paper, Δ=15, which represents a one-second look ahead time. The threshold values for $S_{L,R}(k+\Delta)$=0.4 and $b'_{LEFT,RIGHT}(k)$=0.5, correspond to approximately .8 meters and 1 meter from the center of the vehicle in the ground plane, respectively. The test vehicle used measures approximately 1.75 meters wide.

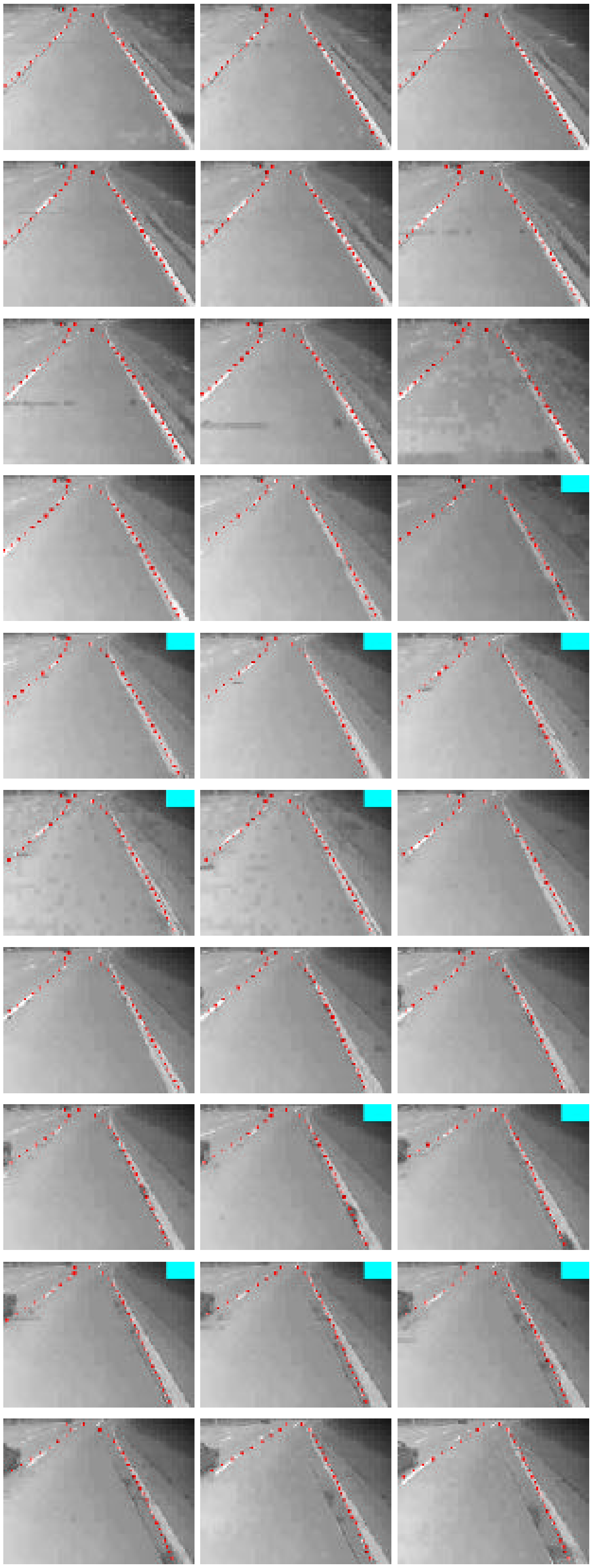

Figure 8. A drowsy driver poorly handling the lane.

VI. Concluding Remarks

The LOIS-based lane tracker provides a very reliable algorithm for the development of a lane departure warning system. The lane departure warning system developed here, namely one that incorporates the estimates of lateral offset with a Kalman Filter for future offset prediction, has been shown to work under a variety of driving scenarios. In the future, such a system could be used not only to warn a driver of an impending lane crossing, but eventually to take control of the vehicle.

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