# A Frequency Domain Approach to Lane Detection in Roadway Images

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## Abstract

*This paper introduces a new algorithm for detecting lane markers in images acquired from a forward-looking vehicle-mounted camera. The method is based on a novel set of frequency domain features that capture relevant information concerning the strength and orientation of spatial edges. The frequency domain features are combined with a deformable template prior, in order to detect the lane markers of interest. Experimental results that illustrate the performance of this algorithm on images with varying lighting and environmental conditions, shadowing, lane occlusion(s), solid and dashed lines, etc. are presented. The algorithm seems to detect lane markers remarkably well under a very large and varied collection of roadway images. An experimental comparison is drawn between this frequency feature-based algorithm and the spatial feature-based LOIS lane detection algorithm.*

## 1. Introduction

Lane detection, the process of locating lanes in an image with no prior estimate to aid the search, is an important enabling or enhancing technology in a number of intelligent vehicle applications, including lane excursion detection and warning, intelligent cruise control, lateral control, and autonomous driving. Studies such as [1][2][3] contain a detailed discussion of these applications and their overall impact on the economy, environment, and driver safety.

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 [4][5][6] 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 (as would be the case when the road has no lane markers, but only pavement edges).

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. ARCADE [6], RALPH [7], and LOIS [8] are typical examples of these second generation systems. Of these, the LOIS lane detector [8] is the most relevant to this paper. LOIS is a template matching algorithm at the heart of which is a likelihood function that encodes the knowledge that the edges of the lane should be near intensity gradients whose orientation are perpendicular to the lane edge. This allows strong magnitude gradients to be discounted if they are improperly oriented and weak magnitude gradients to be boosted if they are properly oriented. There are several other such second generation systems; the reader is referred to [9] for a description of those.

However, not all of the problems associated with the first generation systems have been overcome. In particular, a number of second generation lane detection systems still have a tendency to be "distracted" or "pulled" away from the true lane markers by the presence of strong and structured edges such as those created by a vehicle outline. In portions of the image whose distance from the camera is large, vehicle outlines have a much higher contrast compared to the true lane markers. In such cases, hypotheses that include the vehicle outline as part of the template are more (or at least equally) favored than those that do not include them. The net result is that, although second generation lane detection systems provide a fairly accurate estimate of the vehicle's offset and perhaps even orientation, relative to the true lane markers, their curvature estimates are not reliable.

One way to overcome this problem is to find image features that include the same amount of information about the true lane markers as the image intensity gradient field, which are not as sensitive to extraneous edges. The primary intent of this paper is to report the discovery of such a desirable set of image features (see Figure 1) and to make a systematic comparison of those features to the image intensity gradient field.



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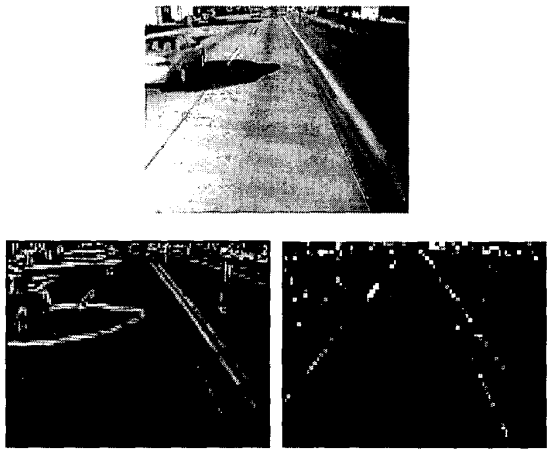


**Figure 1. Top: A typical road image. Bottom Left: The image's gradient field. Bottom Right: The image's new feature vector field.**

The method proceeds as follows: A given image is broken up into 8×8 pixel blocks. For each block, a frequency-domain-based feature vector is computed. This feature vector reflects the amount of "diagonally dominant edge energy" that is contained in that 8×8 block. The block feature vectors are then collectively used in combination with a deformable template shape model of the desired lane markers. This combination is accomplished in a Bayesian setting, where the deformable template model plays the role of a prior probability, and the feature vectors are used to compute a likelihood probability. The lane detection problem is reduced to finding the global maximum of a four-dimensional posterior probability density function, and an exhaustive search is employed to find the global maximum.

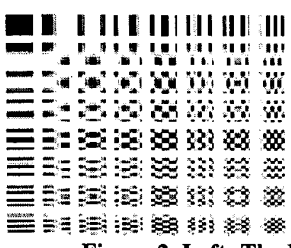
The algorithm was applied to a widely varying set of roadway images–this set includes images obtained under a variety of lighting and environmental conditions, shadowing, lane occlusion(s), solid and dashed lines, and also on a number of images where the LOIS lane detector has problems finding the true lane markers. These results seem to indicate that lane detection in the frequency domain has some inherent advantages over detection in the spatial domain.

## 2. Frequency Domain Features

There are many previously published papers that deal with frequency domain counterparts to spatial domain features [12-21]. Some of these papers [12-15] deal with the problems of texture image restoration, segmentation, and classification using frequency domain features. While others [16-20] use frequency domain features to extract edges and also to achieve edge-preserving image coding/compression [16-20]. References [16], [20], and [21] are the most relevant to this paper. Especially, reference [21] deals with a problem similar to this paper: Curve extraction using a multi-dimensional Fourier transform. Curves are represented in a piecewise linear fashion and linked together via a quadtree. At any given node, the image's intensity profile is used to determine whether or not an edge is present at that node. This is accomplished by using a multi-resolution Fourier transform (MFT). Large regions of the image are first examined in the MFT domain for the presence/absence of edge-like features. If an edge-like feature is deemed present in a certain region, then the region is further subdivided by using the quad tree, and a similar presence/absence decision is made at the lower nodes of the tree. This process is repeated until every pixel in the image has a classification in terms of whether or not it lies on an edge. The MFT is convenient for detecting edge features at multi-resolutions and has been used to detect globally relevant edges in a variety of images. The approach in this paper has some commonality with the one in [21], especially in the use of frequency domain to detect edge-like features and the interpretation of these features' significance in a global context. However, the methods and models employed are vastly different between this paper and [21].

Lane edges are the objects of interest in this work. Recall that the features of interest are those that discriminate between lane markings and extraneous (non-lane) edges. An examination of roadway scenes obtained from a forward-looking vehicle-mounted camera easily reveals that lane markers tend to have "diagonally dominant" orientations in the image plane due to the perspective transformation inherent in the ground plane imaging process, whereas the extraneous edges have no such preferred orientations. This paper finds the frequency domain to be a convenient vehicle to discriminate between edges that are diagonally dominant and those that are randomly oriented. Details follow.

A given image is first divided into 8×8 blocks of pixels. Each of the 8×8 pixel blocks are then orthogonally decomposed in terms of a set of 64 discrete cosine transform (DCT) basis elements. Each of these elements, as seen in Figure 2, correspond to spatial domain edges of a certain strength and orientation. Out of these 64 elements, "diagonally dominant" edges are best represented by a set of 12 – as shown in Figure 2. Figure 3 shows several examples of the "value" of these 12 from the standpoint of lane detection. For each original image in Figure 3, the corresponding feature image is obtained by summing the squares of its 12 special DCT decompositions. As one can see, despite the original image having features/edges of various strengths and orientations, the corresponding DCT feature images contain only information about those edges that are diagonally dominant. The rest of this paper explains how such DCT-based features can be exploited for precisely locating the lane markers.



$$\begin{bmatrix} 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 \\ 0 & 0 & 1 & 0 & 0 & 0 & 0 & 0 \\ 0 & 1 & 1 & 1 & 0 & 0 & 0 & 0 \\ 0 & 0 & 1 & 1 & 1 & 0 & 0 & 0 \\ 0 & 0 & 0 & 1 & 1 & 1 & 0 & 0 \\ 0 & 0 & 0 & 0 & 1 & 1 & 0 & 0 \\ 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 \\ 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 \end{bmatrix}$$

**Figure 2. Left: The DCT basis elements. Right: The coefficients used.**

Note that the frequency domain features adopted in this paper are similar to the ones presented in [20][22]. In [20], these frequency features were used for code-book optimization. Whereas in [22], the objective was to detect faces using these frequency domain features.

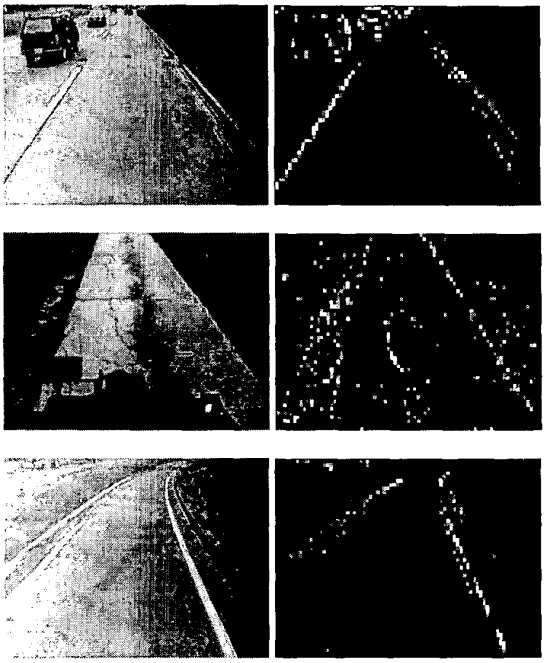


**Figure 3. DCT features of typical roadway scenery.**

## 3. Deformable Template

As mentioned earlier, the algorithm presented in this paper uses a global shape model to predict the manner in which lane markers appear in images. As commonly done [8], this paper also assumes that lane markers 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:

$$x = c * cf * y \qquad (2)$$

and

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

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 eqs. (2) and (3) into eq. (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. While the radius of curvature and tangent orientation of the left and right lane edges will differ slightly, constraining the left and right lane edges to have the same $k'$ and vp parameters closely approximates the actual lane edge shapes for all but very small radii of curvature. As a result, the lane shape in an image can be defined by the four parameters $k', b'_{LEFT}, b'_{RIGHT}, and\ vp$. In summary, the k' parameter is linearly proportional to the curvature of the arc on the ground plane. The vp parameter is a function of the tangential orientation of the arc on the ground plane, with some coupling to the arc curvature as well (depending on the amount of camera tilt). The $b'_{LEFT}$ and $b'_{RIGHT}$ parameters are functions of the offset of the arc from the camera on the ground plane, with couplings to arc curvature and tangential orientation (again, the relative contributions of these couplings depends on the camera tilt) [6]. The flat ground plane assumption is occasionally violated due to a vertical curvature in the road ahead, and also the camera height and tilt changes by small increments due to the suspension rock of the host vehicle. However, accounting for these variations is difficult and also their effect on the accuracy of the detected lanes is not very apparent.

## 4. Bayesian Lane Detection

It is assumed that the values of the lane shape parameters $k', b'_{LEFT}, b'_{RIGHT}$, *and* $vp$ are influenced by a prior probability density function (pdf):

$$P(k', b'_{LEFT}, b'_{RIGHT}, vp) \propto (\text{atan}\,\alpha((b'_{RIGHT} - b'_{LEFT}) - 1) - \text{atan}\,\alpha((b'_{RIGHT} - b'_{LEFT}) - 3) \times \left(1 - \beta\left(\frac{k'}{\chi}\right)^2\right) \quad (6)$$

where $\alpha = 10, \beta = 0.01$ and $\chi = 600$. This prior pdf embodies two types of *a priori* knowledge about roadways: First, roadways tend to have a certain range of widths, and this is enforced by the term involving atans; Second, roadways tend to have a certain range of curvatures, and this is enforced by the parabolic weigting function on k'.

It is also assumed that given the values of $k', b'_{LEFT}, b'_{RIGHT}$, *and* $vp$, the probability of the observed image having the DCT feature values (the ones described in section 2) is given by the likelihood pdf:

$$P(\textit{DCT feature values} \mid k', b'_{LEFT}, b'_{RIGHT}, vp) \propto \sum_{i,j} \sum_{k,l \in C_{i,j}} (dct\_coeff(k,l))^2 \quad (7)$$

where the sum over *(i,j)* covers those $8 \times 8$ pixel blocks through which the left and right lanes (as dictated by $k', b'_{LEFT}, b'_{RIGHT}$, *and* $vp$) pass, $C_{i,j}$ denotes the set of 12 DCT basis elements that capture diagonally dominant edge features (see section 2 for details), and *dct_coeff(k,l)* denote the $(k,l)^{th}$ DCT coefficient of the $(i,j)^{th}$ block of $8 \times 8$ pixels. This likelihood pdf encodes the knowledge that the true lane markers lie along portions of the image that uniformly have a high amount of perspective (diagonally-dominant) edge energy.

These two pdfs are combined using Bayes' rule, and the lane detection problem is reduced to one of finding a maximum *a posteriori* (MAP) estimate:

$$\underset{k', b'_{LEFT}, b'_{RIGHT}, vp}{\text{argmax}} \; P(k', b'_{LEFT}, b'_{RIGHT}, vp \mid \text{DCT feature values}) = \underset{k', b'_{LEFT}, b'_{RIGHT}, vp}{\text{argmax}} \; P(k', b'_{LEFT}, b'_{RIGHT}, vp) \times P(\text{DCT feature values} \mid k', b'_{LEFT}, b'_{RIGHT}, vp) \quad (8)$$

The MAP estimate is eventually found by a straightforward exhaustive search over the 4-dimensional parameter space of $k', b'_{LEFT}, b'_{RIGHT}$, *and* $vp$.

## 5. Experimental Results

The lane extraction procedure described in the previous sections was applied to a varied set of images. The images include those that were obtained under a variety of lighting and environmental conditions, shadowing, lane occlusion(s), solid and dashed lines, etc.

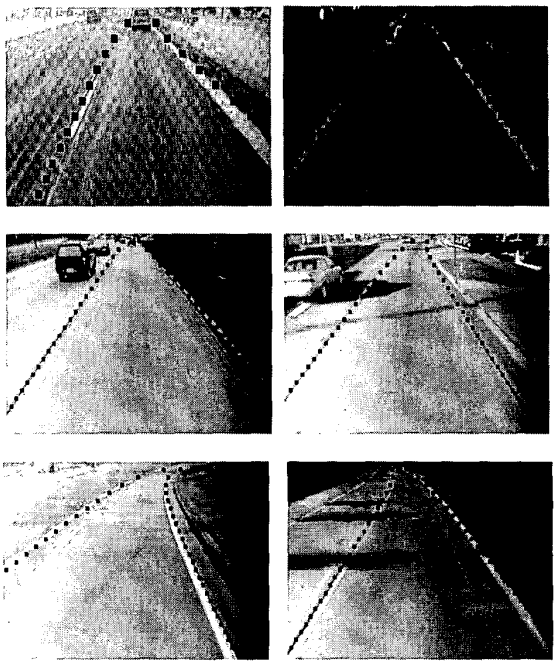


**Figure 4. Example results**

The experimental comparison seems to indicate that this algorithm has some advantages over LOIS. Especially, it does not seem to be distracted by strong non-lane edges in far range.

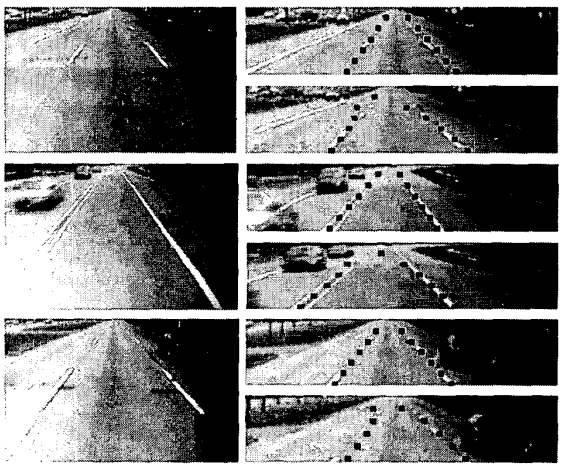


**Figure 5. Experimental comparison.**

## 6. Conclusion

This paper introduced a new Bayesian algorithm for detecting lane markers in images acquired from a forward-looking vehicle-mounted camera. The method was based on a novel set of frequency domain features, and it was shown to consistently detect the unknown lane markers correctly. This was true, even in situations where a more traditional (spatial domain feature-based) algorithm such as LOIS fails. An experimental comparison of the algorithm to LOIS, was undertaken. Future work includes a real-time realization of the algorithm and more extensive testing aboard an automobile.

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