

# Road Singularities Detection and Classification

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**Abstract.** We propose a detection and classification system for various road situations, which is robust to light changes and different road markings. The road curves in an image are described with a Hough Transform, where histograms accumulate the contrast lines for each pixel. The resulting 2D histograms are used to train a Kohonen Neural Network. The final output classification can be used to improve road security, indicating dangerous situations to the driver or feeding a driving control system.

## 1 Introduction

In this work, a sequence of gray-level images will be analyzed, via on-board single camera, in order to describe the road shape. On vision-based intelligent driving-systems, different approaches [2, 7] have been proposed to deal with complex situations such as intersections and junctions. Using a single camera as sensor, a transform as filter, and a non-supervised neural network as classifier, we want to create a simple and fast solution, which is robust for noise, discontinuities, contrast variations, and shadows (Figure 1). The system should be capable of detecting and classifying road singularities, such as shape, relative curve orientation, presence of intersections, etc. A dynamic process may then guide the analysis of the following images in the sequence.



Figure 1: Different image configurations on the same road situation.

The following section describes the implemented method: the Hough Transform, used to detect the road shape, and the Self-Organizing Map (SOM), used

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as classification method. Section 3 gives a quality index for evaluating the training results and its applications on some simulations. The last section presents conclusions and proposals for future work.

## 2 Method

In a system that characterizes objects present in an image, we must first establish a representation that may better describe the information. Previous studies in the literature show that object recognition is improved when it uses the object contours instead of the absolute luminance values (gray levels) [1, 6, 9]. This representation is more robust for local contrasts changes.

### 2.1 Feature extraction

Feature extraction can be seen as a special kind of data reduction for which the goal is to find a subset of informative variables based on image data. Since image data is, by nature, very high dimensional, feature extraction is often a necessary step for object recognition to be successful. It is also a means for controlling the so-called curse-of-dimensionality. When used as further inputs, one wants to extract those features that best describe the objects in the image, preserving the class separability.

Intuitively, road contours may be simplified as a set of curves. Recent works have tried to describe these curves as polynomial equations, splines, etc. [10, 11]. The Hough Transform [5] is a well known technique for detecting lines and curves and extended to other parametric shapes. In this work, we used it to establish a link between a line (or a line segment) of an image from a Cartesian representation to the polar representation using as parameters: the angle  $\theta \in [-180, 180]$  perpendicular to the contrast line (its gradient vector) and the distance  $\rho$  from this line to the center point  $(C_x, C_y)$ . Unlike the classical Hough transform calculus, since we know the orientation of the line, we do not have to accumulate several possible angles and distances, as detailed below [3].

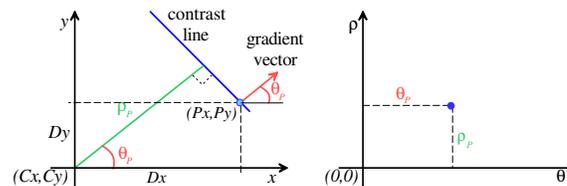


Figure 2: Principle of the vector-gradient Hough transform. Given a pixel  $(P_x, P_y)$  and its local contrast line, the distance between this line and a center point  $(C_x, x_y)$  is calculated using the gradient angle  $\theta$ .

Let the luminance intensity at the image pixel  $(P_x, P_y)$  be  $I(x, y)$ . After a gaussian filtering of the original image, the gradient vector is calculated from

the vertical and horizontal luminance variations between the neighboring pixels:  
 $G_{vertical} = I(x - 1, y) - I(x + 1, y)$  and  $G_{horizontal} = I(x, y - 1) - I(x, y + 1)$ ,  
 respectively, i.e.:

$$\theta = \tan^{-1} \left( \frac{G_{vertical}}{G_{horizontal}} \right) \quad (1)$$

Let  $D_x = P_x - C_x$  and  $D_y = P_y - C_y$ , as illustrated in Figure 2, the distance  $\rho$  from the defined local contrast line (perpendicular to the gradient) to the center point can be calculated as:

$$\rho = D_x * \cos \theta + D_y * \sin \theta \quad (2)$$

Hence, Equations (1) and (2) define a mapping  $(x, y) \in \mathbb{R}^2$  to  $(\theta, \rho) \in \mathbb{R}^2$ .

From the definition, each line (even when discontinuous in the image) becomes a point on the accumulation space, i.e. the new representation. If the curves can be approximated by a set of line segments, then it will be transformed into a cloud of points in the new representation. In particular, intersection curves in the scene will be represented as separated clouds of points.

The result of the feature extraction is a histogram describing the relevant contrast lines on the scene (see Figure 3–A and B). The inverse transformation of the highest points on the histogram gives the main lines of the road curves (Figure 3–C).

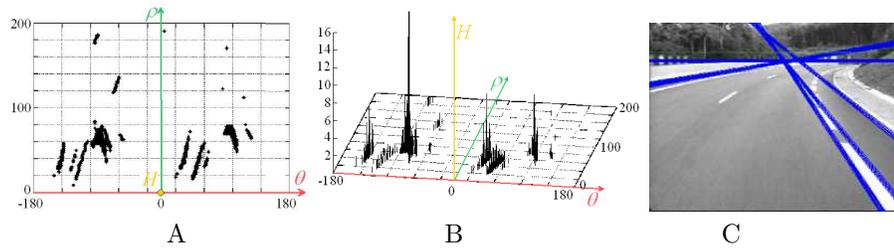


Figure 3: From a gray level image of a turn to the right, the 3D histogram of the  $\theta, \rho$  Hough Transform was extracted (A and B). The inverse transformation is applied on the histogram maxima, allowing us to extract the main lines on the image.

Given that a line is described on the image space by the equation  $y = ax + b$  and that the calculations of  $\theta$  and  $\rho$  may be described as functions of  $a$  and  $b$ , the Hough Transform may be formalized by a pair of functions:

$$\begin{bmatrix} a \\ b \end{bmatrix} \xrightarrow{H} \begin{bmatrix} \theta \\ \rho \end{bmatrix} \quad \text{where} \quad \begin{aligned} \theta &= f(a, b) \\ \rho &= g(a, b) \end{aligned}$$

The Jacobian determinant of the above functions shows that the best way to give weight to the entries is proportional to the gradient vector norm. In this case, the vectors with small norm, the ones more sensitive to noise, have a smaller contribution on the histogram. Besides, null gradient vectors (uniform regions) are automatically eliminated, as shown in the histograms at Figure 4.

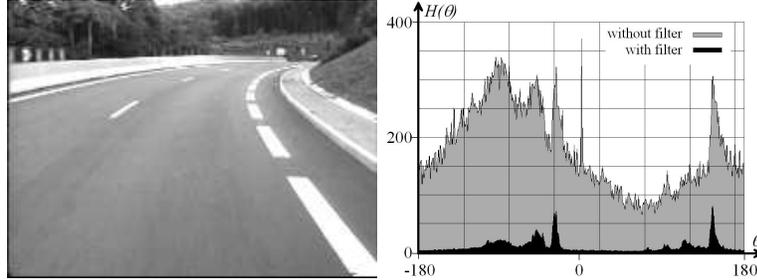


Figure 4: 2D histograms were calculated for the  $\theta$  gradient angles on original image. The gray bars show the noise accumulated on the histogram when adding 1 for each  $\theta$  instance found on the image. The clear peaks appear on the black bars when the vote is proportional to the norm of the corresponding gradient angle.

## 2.2 Classification

A wide class of artificial neural networks can be trained to perform classification. In this paper, we apply a SOM [8] to organize structural road changes in topological manner. The structural information obtained by the previous feature extraction step is collected in a  $d$  dimensional vector  $x$  (where  $d = MAX_{\theta} * MAX_{\rho}$ , the dimensions of the 2D histogram). These vectors are quantized into a finite number of so-called *centroids* using a SOM that offers several advantages such as the ability to quantize adaptively depending on the ranges of the attributes and the ability to deal with the curse-of-dimensionality.

The network has one layer of  $n$  units arranged in a grid. The set  $I = 1, \dots, n$  of units is composed in a topological structure. This is provided by a symmetrical and decreasing neighborhood function  $\Lambda(i, j)$ , defined on  $I \times I$ . The input space  $X$  is included in  $\mathbb{R}^d$ . The units are fully connected to the inputs, and  $x_{ij}$  represents the strength of connection between unit  $i$  and the  $j^{th}$  component of the input. The unit  $i$  is defined by the vector:

$$w_i = (w_{i1}, w_{i2}, \dots, w_{id}) \quad (3)$$

For a given state  $S$ , the network response to input  $x$  is the winner unit  $i_o$ , the closest unit to input  $x$ . Thus, the network defines a map  $\Phi_S : x \mapsto i(x, S)$ , from  $w$  to  $I = 1, \dots, n$ , and the goal of the learning algorithm is to converge to a network state such that the corresponding map will preserve topology. The learning step is formalized by the following equation, where  $\varepsilon$  is the decreasing learning rate.

$$w_i(t+1) = w_i(t) - \varepsilon(t)\Lambda(i_o, i)(x(t) - w_i(t)) \quad (4)$$

Using  $N$  as the number of iterations, we applied the following Gaussian function as a linear decreasing  $\Lambda(i_o, i)$

$$\Lambda(i_o, i) = e^{\left(\frac{-\|i_o - i\|^2}{2\sigma(t)^2}\right)} \quad \text{where} \quad \sigma(t) = 1 + (\sigma(0) - 1) * \left(1 - \frac{t}{N}\right) \quad (5)$$

There are no known proof to the SOM training convergence, but some statistical measures can be made to evaluate the quality of the map [4]. To improve the SOM convergence, we studied the *mean quantization error* during the training with 3 learning rate decreasing functions: linear, exponential and inversed proportional to time (see Figure 5). Given  $\beta$  an initialization parameter, Equation (6) shows the used function.

$$\varepsilon(t) = \varepsilon(0) * \left( \frac{\left(\frac{N}{\beta}\right)}{\left(\frac{N}{\beta}\right) + t} \right) \quad (6)$$

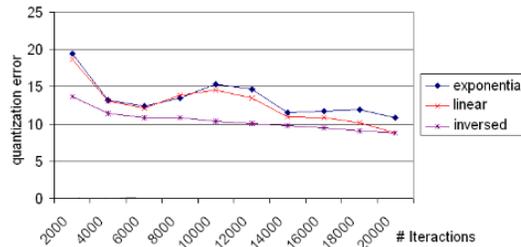


Figure 5: The error evolution (the square distance of an input  $x_i$  and its winner centroid) showed that the best performance is with the inversed decreasing function.

### 3 Simulations

1173 gray scale images, with 384\*288 pixels, were taken from a camera installed on the roof of the experiment car. Several lighting conditions were encountered, depending on the position of the sun and on the shadows provided by trees and various objects. From the continuous recording, we manually selected a proportionally distributed training set of 978 representative images.

The described methodology was applied to each image, and their collected histograms were used as input to the neural network. These histograms were downsampled with a scale of 10, creating input vectors of  $d = (36 * 20) = 720$ . 5 manual labels were established giving a class to each test image: *turn to the right*, *turn to the left*, *straigh road*, *side road junction* and *round-about*. As a supervised step, the test set was presented and centroids class were defined by the label classified more often. The final result of the simulation shows the number images of the labels that were recognized on the same class label:

	Test-set size	Right results	Recognition rate
right	65	55	81%
left	61	44	80%
junction/straight road	59	48	84%
round-about	61	48	72%
Total	246	195	79%

## 4 Conclusion and Future Work

In this paper, we develop a solution for detecting and classifying road singularities. The scene geometry is described by a set of lines, extracted by a Hough transform. These parameters are treated by a SOM network.

The chosen *side road junction* images sequences were always in *straight road* situations. Besides, the lack of contrast and absence of road marks on most of the intersection roads images opened the way to the confusion between the 2 classes. A better set of images should be included on the training set to improve the separability of the classes. The *round-about* sequences represented all the 4 steps of the round-about: approaching, driving in, turning around and driving out. These complex situations create some other confusions. The *round-about* should be splitted in different classes (for example, the turning around seems close to the *turn to the left*).

Although we present a simple supervised output for the SOM clusters, we have chosen the Kohonen map to be able to analyze the behaviour of the sequence classification on the neighborhood topology, in a following step.

New tests with a light/dark band detector show some interesting improvements on the detection the intersection and on the reduction of noise (shadows, textures, etc.). This should be better studied to try to ameliorate the feature extraction.

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