AUTOMATIC LANE DETECTION IN IMAGE SEQUENCES FOR VISION-BASED NAVIGATION PURPOSES

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ABSTRACT:

Intelligent Vehicles, as a main part of Intelligent Transportation Systems (ITS), will have great impact on transportation in near future. They would be able to understand their immediate environment and also communicate with other traffic participants such as other vehicles, infrastructures and traffic management centres. Intelligent vehicles could navigate autonomously in highway and urban scenarios using maps, GPS, video sensors and so on.
To navigate autonomously or follow a road, intelligent vehicles need to detect lanes. It seems that the best cue for lane detection is to use the lane markings painted on roads and it should be noticed that among passive and active sensors, the video sensors are the best candidate for finding lane markings.
In this paper we present a method for lane detection in image sequences of a camera mounted behind the windshield of a vehicle. The main idea is to find the features of the lane in consecutive frames which match a particular geometric model. The geometric model is a parabola, an approximation of a circular curve. By mapping this model in image space and calculation of gradient image using Sobel operator, the parameters of the lane can be calculated using a randomized Hough transform and a genetic algorithm. The proposed method is tested on different road images taken by a video camera from Ghazvin-Rasht road in Iran. Experimental results on different road scenes indicate the good performance of the proposed method.

1. INTRODUCTION

Although the transportation provides the basis for prosperity and progress for each country, it causes some serious problems such as accidents and congestions. For example, according to the Iran's Road Maintenance and Transport Organization (RMTO), about 250000 traffic accidents were reported in 2004 in Iran, resulting in more than 26000 deaths (RMTO website, 2005). For decreasing the negative effects of transportation and improving its efficiency, developed countries are using Intelligent Transportation Systems (ITS). ITS can be considered as a remedy for transportation problems and it has two main categories: Intelligent Infrastructures and Intelligent Vehicles.

Intelligent Vehicles have the potential to enhance road safety, decrease traffic jams and increase the efficiency of transportation. They would be able to understand their immediate environment, communicate with other traffic participants, and could navigate autonomously in highway and urban scenarios using maps, GPS, video sensors and so on. For understanding immediate environment, an intelligent vehicle needs to have some functionality such as lane detection, obstacle detection, vehicle detection and classification, and road sign recognition. These tasks can be performed by active sensors such as radio, acoustic, magnetic and tactile sensors. These active sensors measure quantities, such as distance, in a direct way and generate small amount of data. However, in an outdoor environment, the emitted signals from active sensors may interfere with each other and so decrease the reliability of these systems. In contrary to active sensors, passive sensors can acquire data in a noninvasive way. Probably video cameras are the most important type of passive sensors for ITS applications. In some applications such as lane detection, vision sensors play the basic role and hardly can be replaced with other sensors.

However, in an outdoor environment vision-based navigation accompany by some difficulties intrinsic to the use of vision sensors. For example, illumination in video streams may change drastically because of entering into a tunnel. Hence, the processing should be robust enough to adapt on different road and weather conditions and to tolerate changes in illumination and contrast. Despite its demands and complexity, machine vision offers a powerful way to perceive the immediate environment and widely has been used in intelligent vehicles applications.

Lane detection is an essential component of some intelligent vehicle applications, including Lane following, Lane Keeping Assistance (LKA), Lane Departure Warning (LDW), lateral control, Intelligent Cruise Control (ICC), Collision Warning (CW) and finally autonomous vehicle guidance. Lane detection procedure can provide estimates for the position and orientation of the vehicle within the lane and also can provide a reference system for locating other vehicles or obstacles in the path of that vehicle. In this paper we present a method for lane detection in video frames of a camera mounted behind the windshield of a passenger vehicle. The main idea is to find the features of the lane in consecutive frames which match a particular geometric model. The implemented method is tested on different road scenes in Iran and the results show the success of proposed method in typical road scenes.

2. RELATED WORKS

Vision based lane detection has been an active research topic in the past years and different methods have been presented for solving this problem (Beauvais et. al., 2000; Goldbeck et. al., 2000; Wang et. al. 2004; Bertozzi et. al. 1998). These methods use different lane patterns (dashed or solid), different lane model (2D or 3D, straight or curved, etc.), and also different techniques (Hough transform, template matching, etc.).

Vision based lane detection methods can be categorized in three following classes: region-based, feature-based and model-based.

In region-based methods the lane detection problem is considered as a classification problem. A classification problem consists of feature extraction, feature de-correlation and reduction, clustering and segmentation (Kastrinaki et. al., 2003). In this direction (Turk et. al. 1988) uses color and (Thorpe et. al., 1988) uses color and texture as feature and classify road images into road and non-road classes.

In feature-based methods, firstly some features such as edges are extracted and then these features are aggregated according to some rules and create some meaningful structures (lanes or lane markings). The GOLD system which has been developed at Parma University in Italy is one of the most famous methods in this category. In this method after removing perspective effect using inverse perspective mapping from image, the remapped image is used to detect lane marking with a series of morphological filtering. The extracted features are concatenated and then the poly-lines that are likely to represent lane marking will be selected (Bertozzi et. al., 1998).

Most of vision-based methods for lane detection are model based. They use a geometric model to characterize the lane. These approaches aim to match the observed images with a hypothesized road model. The simplest road model is straight line. An example of such system is represented in (Kenue, 1989). Wang et. al. represented more flexile approaches using snakes and splines to model lane boundaries (Wang et. al. 2004; Wang et. al. 2000). The B-spline based lane model is able to describe wider range of lane structures involving S-shape lane boundaries. Most of algorithms such as algorithms represented in (Liu et. al., 2003; Kluge et. al. 1995; Kluge et. al. 1994; Li et. al., 2004) assume that pavement edges and lane markings can be approximated by circular arcs on a flat ground plane. Some authors such as Dickmanns et. al. and Guiducci applied more complicated models to represent 3D model of lane boundaries (Dickmanns et. al, 1992; Guiducci, 1999) .

3. OUR METHODOLOGY

Using a model in lane detection problem can result in more robustness where edge points are contaminated with noise edges from shadows, cracks, etc. The method represented here is a model based method. It uses a geometric model to represent the lane boundaries. By mapping this model into image space (camera coordinate system) and then using the extracted edges of road image, the method can estimate the geometric lane parameters. The geometric model of the lane has four parameters. We use a randomized Hough transform to estimate two parameters of lane model. Then by optimization of a

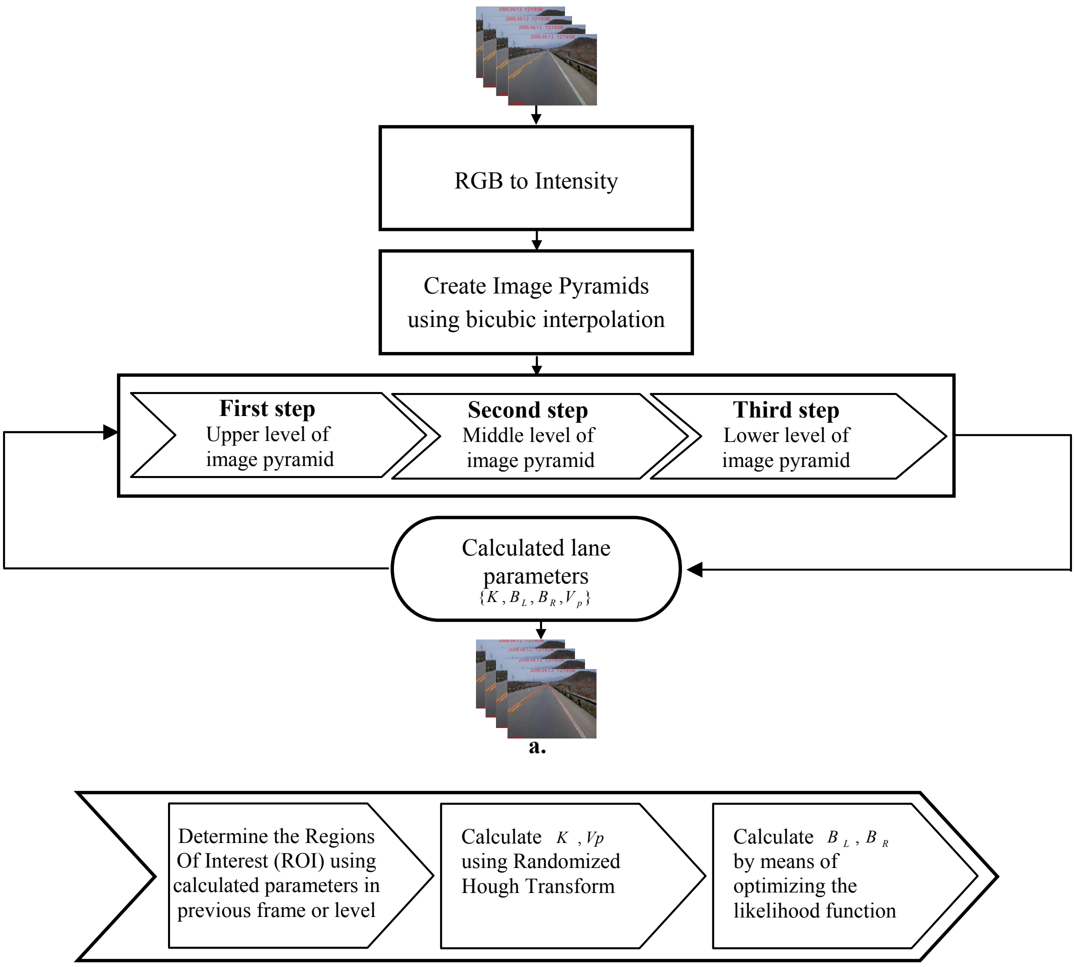

Figure 1. (a) diagram of our methodology, (b) details of first, second and third step

likelihood function using Genetic Algorithm, the rest of parameters will be calculated.. Optimizing a likelihood function for estimating the rest of parameters can enhance the robustness of method because it applies some constraint on lane models.

Figure 1 shows the diagram of our methodology. As can be seen in figure 1, at first the RGB colour image is converted to an intensity image and the rest of operations are performed on intensity image. Then, using a bi-cubic interpolation a three-layer pyramid of image is constructed. After that, by means of the calculated parameters in previous frame, the Regions Of Interest (ROI) in upper level of pyramid is determined. In upper level, the edge pixels in ROI are used by a randomized Hough transform to estimate the curvature and tangential orientation parameters. The rest two parameters are calculated by means of optimizing a likelihood function with Genetic Algorithm. After calculation of all parameters in upper level, the next step is to determine the Regions Of Interests in middle level exploiting four calculated parameters in upper level. This procedure is applied to lower levels of image pyramid. The final parameters calculated in lowest layer are the lane parameters and used for determining the ROI in the next frame. In the first frame where no information exists from previous frame, all pixels of upper layer image are considered as ROI.

The parameters in upper level are determined coarsely. While we go toward the lower level, the resolution of Hough space will increase till to reach a desired accuracy.

More details of this procedure are described in following sections.

3.1 Geometric lane model

The geometric lane model plays an important role in lane detection problem. In fact, the lane model imposes some assumptions about real lane in order to extract 3D information from 2D images. A conventional model for lane is a circular arc on a flat ground plane. In this paper we use this model for representing the lane. In the following we describe more details and the formulation of this model.

Figure 2 shows the schematic view of lane model and relevant coordinate systems. For small to moderate lane curves a circular arc of curvature k can be approximated by a parabola (Kluge, 1994):

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

Equation (1) describes lane model in object space. The projection of this model into image space is as follow. Without losing the generality, assume the camera has no tilt i.e. $\theta = 0$. Using perspective geometry the point (x, y) in object space

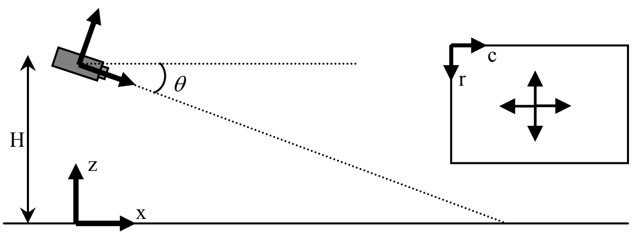

Figure 2. Ground and image coordinate systems

corresponds to pixel (r, c) in image space (see Fig. 1) according to these equations:

$$\frac{x}{H} = \frac{1}{r \times r_f} \qquad (2)$$

$$\frac{x}{y} = \frac{1}{c \times c_f} \qquad (3)$$

Where H = the height of camera,
r_f = height of pixels divided by focal length,
c_f = width of pixels divided by focal length $r = 0$ is the row which corresponds to horizon.

Using some simple algebraic operations, the projection of lane model in image space is as follow:

$$c = \frac{0.5 \times k \times H}{r_f \times c_f} \times \frac{1}{r} + \frac{b \times r_f}{H \times c_f} \times r + \frac{m}{c_f} \qquad (4)$$

Or in abstract format:

$$c = K\frac{1}{r} + B_{L,R} r + M \qquad (5)$$

Where

$$K = \frac{0.5 \times k \times H}{r_f \times c_f}$$

$$B = \frac{b \times r_f}{H \times c_f}$$

$$M = \frac{m}{c_f}$$

In the case of tilted camera, the derivation is more complicated but the final equation in image plane is the same as equation (5) as illustrated in (Kluge, 1994). So the lane detection problem is become the problem of finding the four parameters $\{K, B_L, B_R, M\}$ in equation (5).

3.2 Randomized Hough transform

Hough transform is a popular method for extracting parametric curves from images. It was first introduced by Hough in 1962 for finding lines in images. Today, there are different extensions of Hough transform which are applied in different applications. Randomized Hough transform is an extension of Hough transform in which a set of n pixels is randomly selected from the edge image for determining the n parameters of the curve. In this paper we use the randomized Hough transform to estimate the curvature and tangential orientation of lane model.

In voting procedure of randomized Hough transform, the pixels would be selected based on theirs weights. Weight of each pixel (i,j) is as follows:

$$w(i,j) = \frac{gm(i,j)}{\sum_{r=1}^{R}\sum_{c=1}^{C} gm(r,c)} \quad (6)$$

Where gm = gradient magnitude of each pixel.

Gradient magnitude and gradient direction are calculated by means of Sobel operator.

The weight for each pixel in ROI is calculated and then based on these weights, two pixels will be selected and K, M parameters will be calculated by following equations.

$$K = \frac{(u_1 - u_2) + gd(u_1, v_1) \times (v_1 - hz) - gd(u_2, v_2) \times (v_2 - hz)}{2 \times (\frac{1}{v_1 - hz} - \frac{1}{v_2 - hz})}$$

$$M = u_1 - \frac{2K}{v_1 - hz} + gd(u_1, v_1) \times (v_1 - hz) \quad (7)$$

Where u = column number of selected pixel
v = row number of selected pixel
hz = row number of horizon
gd = gradient direction

Then, the corresponding array of accumulator in Hough space will be increased by 1. This procedure will be repeated for n couples of pixels.

To increase the efficiency of proposed algorithm, we use a multi-resolution strategy to estimate lane parameters so that we can estimate lane parameters coarsely and increase quantization accuracy in each level till to reach the desired accuracy for parameters.

3.3 Likelihood function

The likelihood function determines how well a hypothesized lane is match with road image. In this method we use a likelihood function introduced by Kluge et. al in (Kluge et. al., 1995). This likelihood function is used for estimating B_L, B_R parameters.

The intuition underlying this likelihood function 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 (Beauvais et. al., 2000). This likelihood function operates on raw image gradient information without the need for explicit thresholding to select edge points.

Mathematically, we can define a penalty function as follows:

$$f(\alpha, x) = \frac{1}{1 + \alpha x^2} \quad (8)$$

Where α determines how fast $f(\alpha, x)$ decreases as x increases.

Then the contribution of each pixel to the likelihood value is equal to (Beauvais et. al., 2000):

$$gm \times f(\alpha_1, Dist_{pixel}) \times f(\alpha_2, \cos(gd - TempTgt)) \quad (9)$$

Where $Dist_{Pixel}$ = the distance in columns from the closest lane edge (left or right)
$TempTgt$ = the tangential orientation of the closest template lane edge calculated for the pixel's row.

3.4 Optimization using Genetic Algorithm

We used the Genetic Algorithm (GA) to find the global maximum of likelihood function. Other global optimization method such as exhaustive search or simulated annealing can be used instead of Genetic Algorithm.

The Genetic Algorithm is an optimization and search technique based on the principles of genetics and natural selection. It repeatedly modifies a population of individual solutions. At each step, the genetic algorithm randomly selects some of individuals from the current population to be parents and use them to generate next population. To do this, a typical GA uses three main operations namely *Selection*, *Cross Over* and *Mutation.*

In our implementation, the number of individuals in each population is 25 and the number of generations is 20. At first generation, the population is selected uniformly and in other generations the selection is based on the cost of individuals. We used a blending function introduced by (Haupt et. al. 2004) for crossover operator and also another blending function for mutation operator. For more details of these operators see (Haupt et. al. 2004).

4. EXPERIMENTAL RESULTS

To test the proposed methodology for lane detection, we captured video frames from Qazvin-Rasht road in Iran using an onboard CCD camera mounted behind the windshield of a passenger car. The frame rate of video images was 5 frames per second and the resolution of each frame was 200×240. We captured the images of this road from beginning to the end of this road and the total time of our data was about 4 hours.

Qazvin-Rasht road is a typical road in Iran and different weather and lighting conditions can be seen along this road including dashed or continuous lane markings, white or yellow lane markings, curved or straight lanes, flat or non-flat lanes, two-lanes or multi-lanes roads, stains and puddles on road surfaces. Some tunnels are located at this road and so we were able to test our methodology on images taken while the vehicle enters into or exits from tunnels.

Some of the experimental results of lane detection methodology are shown in Figure 3. These images represent different real

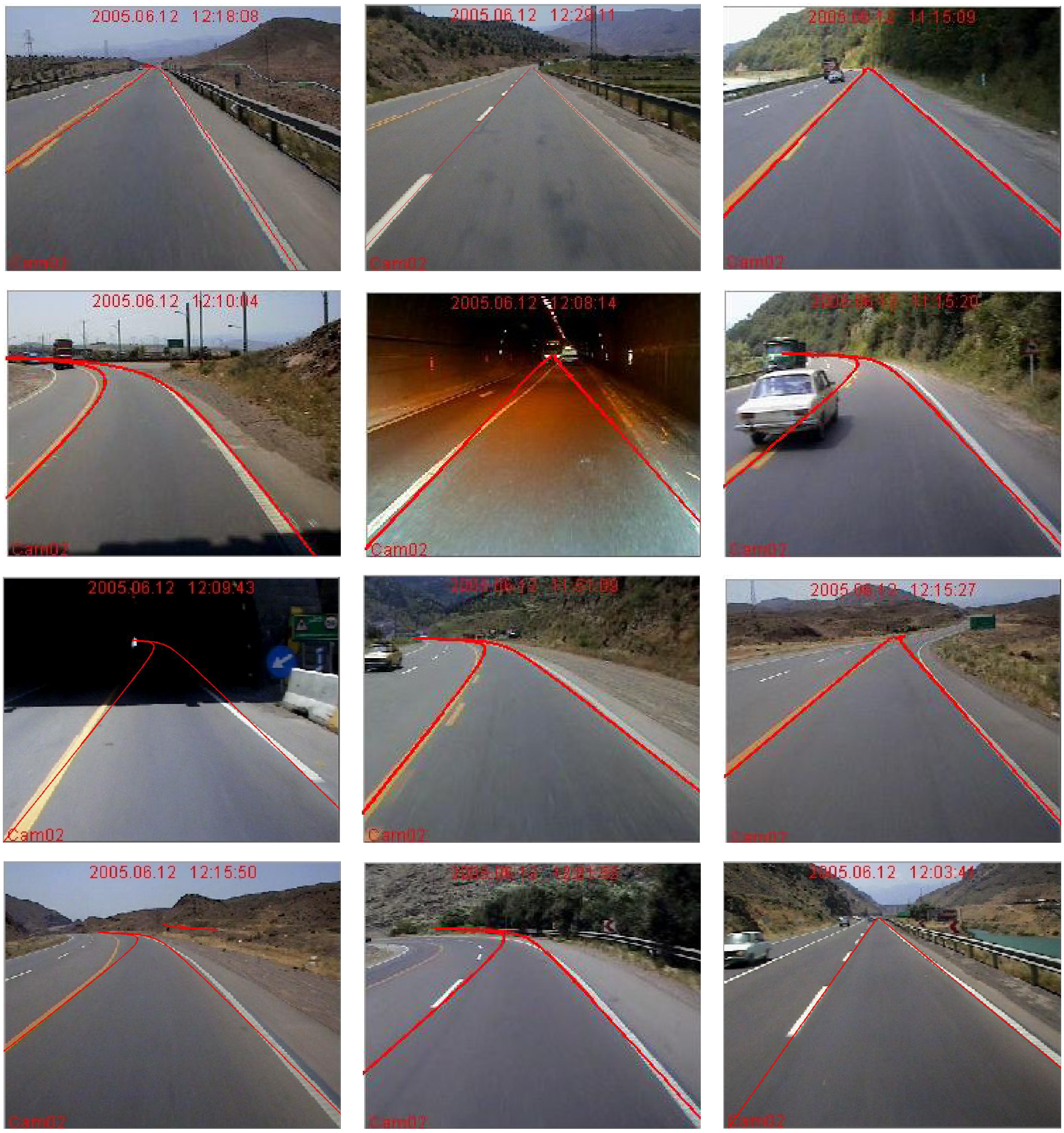

Figure3. Experimental results

road scenes. It can be seen that, the method generally works good enough on these images. In one of these images, the lane marking is occluded by other vehicles but the lane is appropriately detected. Also the method has detected the lane correctly in the image taken while the vehicle enters into the tunnel. There are some deviations in far part of some images which are due to the flat earth assumption that we made on lane model and poor quality of video frames.

5. CONCLUSIONS

For autonomous navigation of intelligent vehicles in highway and urban scenarios, they entail to detect lanes. In this paper we presented a methodology to detect lanes in video frames. The proposed method uses a parabolic lane model to represent lanes in each video frame. Then, by means of randomized Hough transform and a Genetic Algorithm, it estimates the parameters of lane model. The proposed method is tested on different road scenes and a reasonable performance is achieved. However, for using this method in intelligent vehicles applications, where high reliability is demanded, it needs hardware implementation and a lot of time for testing.

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