

REAL-TIME AUTOMATED ROAD, LANE and CAR DETECTION for AUTONOMOUS DRIVING

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ABSTRACT

In this paper, we discuss a vision based system for autonomous guidance of vehicles. An autonomous intelligent vehicle has to perform a number of functionalities. Segmentation of the road, determining the boundaries to drive in and recognizing the vehicles and obstacles around are the main tasks for vision guided vehicle navigation. In this article we propose a set of algorithms which lead to the solution of road and vehicle segmentation using data from a color camera. The algorithms described here combine gray value difference and texture analysis techniques to segment the road from the image, several geometric transformations and contour processing algorithms are used to segment lanes, and moving cars are extracted with the help of background modeling and estimation. The techniques developed have been tested in real road images and the results are presented.

Key words: Autonomous driving, computer vision, lane detection, intelligent vehicles, background modeling.

1. INTRODUCTION

An autonomous ground vehicle is a vehicle that navigates and drives entirely on its own without a human driver. Through the use of various sensors and positioning systems, the vehicle learns about its environment and carries out the task it has been assigned. Camera-assisted navigation is very crucial in autonomous intelligent vehicle applications. A common approach to solve autonomous vehicle guidance problems is to place a single camera mounted inside the car, looking to the road ahead. A sample setup is shown in Figure 1:

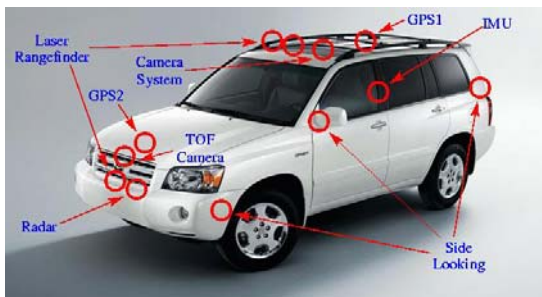


Figure 1.0 The car setup by Ohio State University prepared for DARPA Urban Grand Challenge [11]

The reasons behind this set up are:

- The camera would be safer and less effected from the outer world condition fluctuations.
- Having a single camera leads to a more economical system,
- Camera is mounted inside the vehicle with attention not to interfere with the vision of the driver.

However, there are unavoidable disadvantages in this convenient set up as well:

- In front of the lens another layer (the windshield) is inserted artificially. This new layer leads in many occasions to reflections and introduces false alarms.
- The distance to road increases, which, in turn, the precision of the algorithms developed is decreased.

To bring a solution to these generic problems, a set of algorithms are proposed, which include road, lane, and car detection, particularly for guiding the vehicle at intersections. Section 2 gives the background on the methods used in developing the framework. In section 3, the experimental results are discussed and in section 4, the conclusion and future work are presented.

2. METHODS

2.1 Asphalt Detection Algorithm

To be able to segment the asphalt (asphalt represents the road itself), image is first cropped into a smaller region for fast processing. This region is normally defined beforehand. Then, for reducing the noise in the signal and making the algorithm more resilient, image is filtered with a mean-filter or a non-recursive Gaussian filter. To speed up the processing, a simple 3x3 mean filter is used in the current work.

We have merged segmentation and texture modeling to classify the image into different regions of interest and to identify the asphalt.

2.1.1 Segmentation

We have used the simultaneous region growing technique for segmentation [10]. The idea behind simultaneous region growing technique is to choose a certain number of seed pixels in the image and start connecting the pixels in the neighborhood if the predefined similarity measure is satisfied. The region

is said to be grown from a seed pixel by adding new pixels that are similar, which causes the region to enlarge. When the growth of certain region stops we move onto another one. This process is parallelized by choosing multiple number of seeds. The overall process continues until all the pixels belong to some region. The basic reason to choose multiple seeds is to prevent a region from over-growing and to dominate the proceedings. In addition, a dual core CPU can run this process in parallel to speed up.

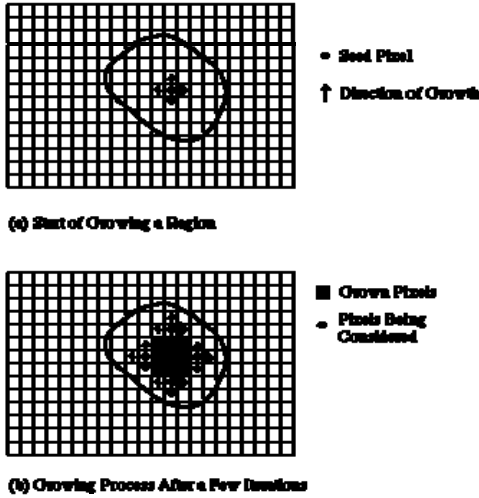


Figure 2 Illustration of the simultaneous region-growing algorithm

2.1.2 Law's Texture Analysis

To accomplish a satisfactory extraction of the asphalt, the texture information is analyzed. The texture segmentation is done by applying s and e filters [7], which operate row-wise first and column-wise later:

$$e = [-12021], \rightarrow s = [-10201] \quad (1)$$

In other words, the image is first convolved with e along the rows. The resulting image is convolved with e , this time column-wise, which yields the EE-filtered texture image. This operation is repeated with the s mask similarly forming the SS-filtered texture image. To compensate for errors and make texture more pronounced, a median filtering is applied on both images. The convolution of the mask $h[k,j]$ with the image $x[r,c]$ signal is defined as follows:

$$\sum_{k=0}^{M-1} \sum_{j=0}^{M-1} h[k,j] * x[r-k, c-j] \quad (2)$$

2.1.3 Learning Texture of the Asphalt

A simple 2-D learning algorithm has been devised to classify the image with respect to texture. A 2-D histogram of the EE and SS images of the asphalt texture are computed, where gray levels of one of the two channels form the x-axis and those of the other

channel form the y-values of the 2-D Histogram. A morphological closing operation has been performed on this 2-D histogram to create a generic histogram classifier which is to cover all the texture variations that are faced. From this point further, the 2-D histogram data will be referred as the feature space.

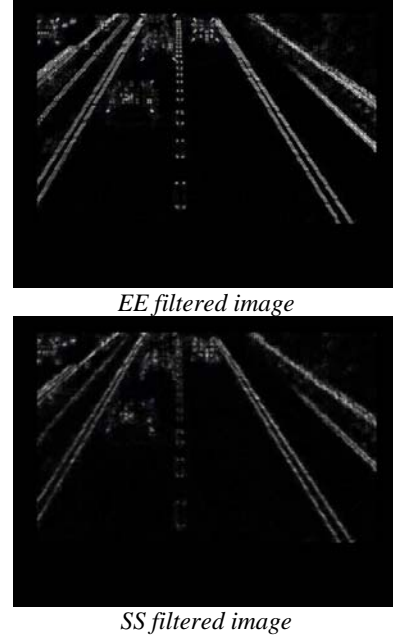


Figure 3 Result of applying Law's texture filters to road images

2.1.4 Classification of Asphalt Texture

When a new image arrives, the texture segmentation is employed to generate the texture structure in terms of SS and EE images. Next, a supervised pixel classification is performed on these two channels. In other words, the new pixels are compared one-by-one against the feature space to check if the new pixels belong to the asphalt texture or not.

2.1.5 Merging Two Outputs

The simplest way to fuse the information of region-growing and texture analysis is to take the intersection of the output regions. The output of the simultaneous region-growing algorithm is separated and labeled into regions which have similar gray values (or other predefined similarity measure). The output of the texture analysis is simply a region containing the pixel locations that have the asphalt texture.

Finally, if the grown regions are intersected with the texture segmented region, and we take all the regions that are 8-connected and labeled the same way at the end of region growing, we obtain the asphalt region.

Notice that throughout the whole process, no color or gray-level based segmentation or classification is performed. Only the gray-level similarities and the

textures are classified and taken into account. This makes the algorithm more robust against illumination variations.

2.2 Lane Detection Algorithm

Lane detection is a well-researched area of computer vision with applications in autonomous vehicles and driver support systems. [6,9] Despite the perceived simplicity of finding white markings on a dark road, difficulties arrive from shadows, occlusion by other vehicles, changes in the road surfaces itself, and differing types of lane markings. However, in our case, having segmented the road first gives us ideas about where the lanes can lie. But, one has to keep in mind that if there is heavy traffic it may be impossible to segment the asphalt perfectly and lane detection could still pose a problem. For such cases a simple but effective algorithm has been proposed.

2.2.1 Lane Contour Detection

Lane detection algorithm is composed of Canny edge detection, contour extraction and Hough transform.

a. Canny edge detection is performed on the image to extract the contours of the edges.

After, canny edge filtering, we make an 8-connected component analysis and classify the different regions according to their contour lengths and include only the ones that are long enough to be a lane.

At this point, the “lane candidates” are obtained. Because curvatures (in this case, lanes) can be considered as lines in very small intervals, a robust line fitting is performed.

The idea in robust fitting is to minimize a robust function of the residuals iteratively subject to the parameter vector, \vec{a} , i.e. minimize

$$\sum_{i=0}^n \rho[y_i - f(\vec{x}_i, \alpha)] \quad (3)$$

We have chosen the ρ function to be the Tukey’s function. [8]

The next step is the Hough transform [10]. Hough transform is the most commonly used technique for the detection of regular curves such as lines, circles, ellipses, *etc.* The idea for Hough transform is based on the fact that curves generated by collinear points in the gradient image intersect in peaks (r, θ) in the Hough transform space where the equation for describing a set of lines is given by:

$$x \cos \theta + y \sin \theta = r \quad (4)$$

This equation specifies a line passing through (x, y) that is perpendicular to the line drawn from the origin to (r, θ) . By thresholding the resulting image in the

Hough transform space, the lines that pass through corners or edges in the image are located. Corners or edges should be considered as the peak points where most of the lines pass through.

Even though the lanes have curved geometry, Hough Transform will still give us a good approximation, approximating curvature as a constantly changing sequence of lines.

This approach results in a good approximation of the lane, without using the asphalt information.

2.3 Car Detection

New vehicle detection and surveillance technologies are constantly being developed and existing technologies improved, to provide speed monitoring, traffic counting, presence detection, headway measurement, vehicle classification, and weigh-in-motion data. (See [4] for a comprehensive survey). Since our main interest lies in analyzing the traffic at intersections, the car detection algorithm developed has the assumption that the autonomous vehicle is at rest and wants to understand the traffic movement around.

A movement detection system based on Kalman Filters has been implemented for detecting moving cars around. After the estimation of the movement, the image is separated into 8-connected components and the regions that occupy a predefined area are selected. These are classified as large moving objects, representing the cars, in most cases.

3. EXPERIMENTAL RESULTS

The asphalt detection algorithm is robust against slight illumination changes. The reason is that neither the texture analysis nor the region growing algorithm is strongly affected by fluctuations in illumination conditions. However, for this technique to be effective, the road should be visible enough for asphalt finder to perform as expected.

Kalman Filter is tuned to detect motion when there is significant movement. Optical flow and vector fields techniques would perform better for slight movements not taking the prior information into account.

The algorithms developed have been applied to several video images that are obtained in the Drive-safe project [1]. The examples selected include images that are taken at different times and different sections of the route which portray different asphalt conditions. Some results are shown in Figure 4:



Original image 1



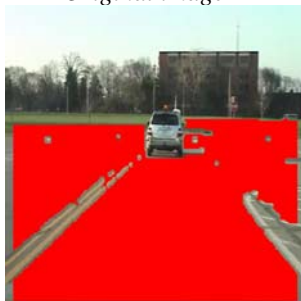
Asphalt segmentation 1



Asphalt segmentation and car detection



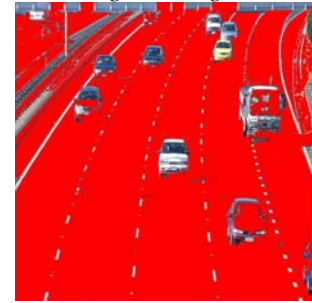
Original image 2



Asphalt segmentation 2



Original image 3



Asphalt segmentation 3



Original Image 4



Asphalt and lane detection 4

Figure 4 Experimental results for asphalt extraction, car and lane detection

4. CONCLUSIONS and FUTURE WORK

In this paper a framework for generic autonomous vehicle vision applications is presented as a basis for algorithms that should come on top of this framework. Texture and the gray value similarities have been combined to improve the accuracy of the analysis.

Future work will include locating the intersections and identifying the other vehicles present around the intersection. Lane tracking will be added in order to use the information of the previous frames for improving the accuracy of lane detection..

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