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Road Lane Detection for Autonomous Robot Guidance

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***Abstract* - Computational Vision stands as the most comprehensive way of knowing the surrounding environment. Accordingly to that, this study aims to present a method to obtain from a common webcam, environment information to guide a mobile differential robot through a path similar to a roadway.**

Keywords - Robotics, Mobile Robots, Autonomous Driving, Computer Vision, Image Processing and Image Recognition.

I. Introduction

Mobile robotics and particularly the area dedicated to autonomous robot guidance, remains as one of the robotics sectors with more activity, promoted essentially by the constant development of systems capable of being used in vehicles as a way to improve their safety and comfort.

Such systems, sensorial dependent, provide ability to autonomously follow a path, like a roadway, while avoiding obstacles and respecting the existing signaling. Real-time lanes detection is a common task to these systems, being also the element that affects more significantly the whole control process.

The detection, supported in computer vision algorithms, consists in the localization of the road, the determination of the relative position between vehicle and road and in the analysis of the vehicle's heading direction. The unpredictability of the environment where it is performed, makes it a challenging task, which motivate many researchers in this area.

Different methods are used for lane detection and tracking like [15], where it is proposed a method based on lane geometrical features associated with the geometrical relationship between camera and road, [4] where authors suggested a framework fusing color, texture and edges to recognize the lane of country roads or [7], an approach based on Hough Transform.

This work emerged from the evaluation of a method, sustained in a webcam and composed by several image processing and recognition steps, centered only in road lane markings, which could provide a simple but accurate information to a controller in a way that can be used directly to guide a robot in a path similar to a roadway.

In order to test the correctness of the implemented vision system a Fuzzy controller was used to control the robot motors [11]. Taking advantage of implementation simplicity, which eliminates system modeling by using only the empirical knowledge about its behavior, was possible to develop a functional system that can be easily adapted to other mobile platforms with similar characteristics.

II. Hardware

To test the proposed methodology, it was implemented in a differential robot, composed by a platform that support two permanent magnets electric motors (24V DC), batteries, controller boards, webcam and the control computer.

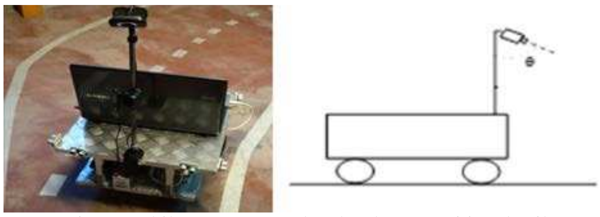

Fig. 1 Mobile structure used and webcam position detail

III. Methods and Algorithms

This chapter describes methods and algorithms required to implement the road lane detection algorithm that will be the basis for the robot guidance system. An efficient image processing algorithm is essential for a good overall system performance.

Image acquisition and interest areas definition

Normally, when Computational Vision is used for a given task, the acquired images contains quite unnecessary information to process. A way to make the subsequent tasks of detection and extraction quicker is to avoid the information without meaning to be also processed. For this, the acquired image, with a 640x480 pixels resolution, is usually divided in blocks and consequently, the processing steps are restricted to specific areas.

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In this work, it is essential to detect independently each of the lanes. Because of this, image processing related to road lanes is made in two separate image areas, with predetermined size, which correspond to areas where in each moment is expected useful information for the application in question.

To maximize efficiency, the interest areas position depends on movement speed. Higher speed implies detection in the upper zone of the image, which in practice corresponds to a detection further away from the robot.

The implemented methodology allow the use of other capture equipment, without pre-calibration. For this, entire image processing is based on absolute pixels distances.

Depending on the speed, the interest area position is given by the following equation:

$$Pos = Pos_{min} - 45(vel - 1) \tag{1}$$

Where *Pos* is the determined height for interest zones top corners, Pos_{min} is the height (360 pixels height) at minimum speed (1 cm/s) and *vel* corresponds to the speed of movement at any given moment. The constant used in eq. 1 (45) establish the robot maximum speed and its relation to the possible interest areas.

In Fig. 2 the interest areas position for the minimum speed value are drawn. The arrows indicate the movement of these areas in response to a velocity increase.

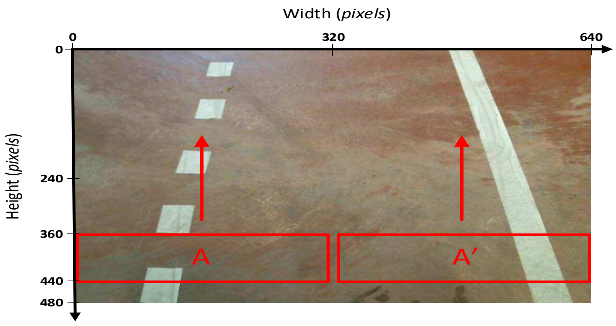


Fig. 2 Interest areas position

Gaussian filtering

Real image acquisition is a very sensitive process to outside influences, sometimes the information is degraded in such a way that it becomes unusable. Frequently, to minimize this type of situation it is used some sort of filtering and smoothing techniques.

The image processing performed in this work, primarily focused on detection of contours, is very sensitive to noise. The application of a low-pass filter, smooths the image without eliminate relevant information.

Among the most used low-pass filters, can be highlighted the mean filter [2] and the Smooth Gaussian filter [1]. In this study it was used the Smooth Gaussian filter [1] due to the different weights for each position of the filtering mask applied to the image, which allows the image contours preservation.

The application of a Smooth Gaussian filter [1] to an image is based in a Gaussian function. The next equation corresponds to a two dimensional Gaussian function:

$$G(x,y) = \frac{1}{2\pi\sigma^2} e^{-\frac{x^2+y^2}{2\sigma^2}} \tag{2}$$

Mathematically, the implementation consists in the image convolution with a mask (Fig. 3) determined by the Gaussian function indicated previously. The filtering depends of σ (standard deviation) and mask (convolution window) size. In this work it was applied a two dimensions Gaussian filter, with a 3x3 mask size and σ=1, example result on Fig. 4.

$$\frac{1}{13}\begin{array}{|c|c|c|}\hline 1 & 2 & 1 \\ \hline 2 & 3 & 2 \\ \hline 1 & 2 & 1 \\ \hline\end{array}$$

Fig. 3 Gaussian filter mask - 3x3 and σ=1

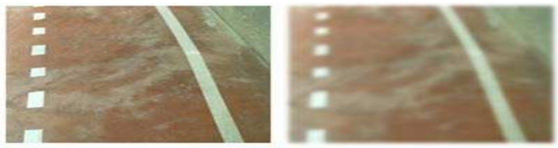


Fig. 4 Gaussian Filtering (Original – Left, Filtered – Right)

Grayscale

The image recognition inherent to this work implies the use of black and white images. Image binarization is performed after grayscale conversion in accordance with BT.709-5 of 2002 of ITU-R [14], which consists in the equation:

$$Gray(x,y) = Red(x,y) \times 0.299 + Green(x,y) \times 0.587 + Blue(x,y) \times 0.114 \tag{3}$$

Binarization

Binarization is the simplest segmentation method and consists essentially in the separation of regions according to their importance for further processing. This separation, based on the choice of a threshold, highlights certain aspects of the image at the expense of others irrelevant to the application.

Automatic Threshold determination

In dynamic environments, an automatic method for determining the optimal threshold for binarization / segmentation is what leads to better results.

Several authors have implemented solutions for automatic thresholding like Huang [6] and Li [8]. In this work, the similarity of results, the ease of implementation and the low computational load involved in the execution, made an approach based on the method presented by Otsu [10] the appropriate option for the image processing necessary for this application.

The method proposed by Nobuyuki Otsu [10] considers that the image has two classes of pixels, the background - set of pixels with gray intensity below the threshold - and the foreground - pixels with intensity above the threshold, and determines the optimal threshold by an exhaustive search by the value that maximizes the variance between classes.

Designating the background pixels class by C_1 and the foreground pixels class by C_2, the variance between classes, σ_e^2, for a specific threshold k can be determined by:

$$\sigma_e^2(k) = P_1(k)P_2(k)[\mu_1(k) - \mu_2(k)]^2 \tag{4}$$

Where:

$$P_1(k) = \sum_{i=0}^{k} p_i \tag{5}$$

$$P_2(k) = \sum_{i=k+1}^{L-1} p_i = 1 - P_1(k) \tag{6}$$

$$\mu_1(k) = \frac{1}{P_1(k)} \sum_{i=0}^{k} i p_i \tag{7}$$

$$\mu_2(k) = \frac{1}{P_2(k)} \sum_{i=k+1}^{L-1} i p_i \tag{8}$$

With:

$$p_{i=} \frac{n_i}{M \times N} \tag{9}$$

Where n_i is the number of pixels having the gray intensity, i, L is the number of gray levels and $M \times N$ is the dimension of the image.

Therefore, based on eq. 4, the optimal threshold value for the binarization, k^*, results of:

$$k^* = \max_{0 \le k \le L-1} \sigma_e^2(k) \tag{10}$$

The determination of the inter-classes variance in relation to the gray level k, will serve as difference measure. The threshold that maximizes the difference will be the most suitable to perform the binarization of the image in question.

Road lane detection

After splitting the image and processing the resultant areas, is time to initiate the fundamental image feature extraction, the recognition of shapes.

This step provides the necessary information for robot guidance and positioning. The shape detection becomes possible identify unambiguously road lanes characteristics such as area, perimeter and center. With these characteristics, determining the relative position of the central axis of the robot towards its goal (central roadway axis) proves to be a fairly simple task.

Over the years, several methodologies have emerged, being the great majority based on contours/borders detection, which, as it can be seen in earlier work [12] in this area, as well in recent developments [5], support this analysis in the following and classification of contours.

In this work it is implemented an algorithm for shapes detection based on the solution proposed by Satoshi Suzuki and Keiichi Abe, which is supported in border following and classification, and remains as a good compromise between effectiveness and speed [13]. The proposed method consists essentially in successively and hierarchical classification of pixels in a binary image. It starts a sequential pixel analysis that follow until one of the conditions indicative of a contour presence (eq. 11) is found

$$f_{ij} = 1 \; and \; f_{i,j-1} = 0 \; or \; f_{ij} = 1 \; and \; f_{i,j+1} = 0 \tag{11}$$

Being $f_{ij}, f_{i,j-1} \; and \; f_{i,j+1}$ pixels at different positions.

When this occurs, that pixel is considered the contour starting point, and the classification process, centered in pixel neighborhood analysis starts. After following a contour, the global image analysis resumes at the contour starting point.

In Fig. 5 is represented an illustration of a contour following by the implemented method. The red square represents the contour starting point in a 5 x 5 pixels image.

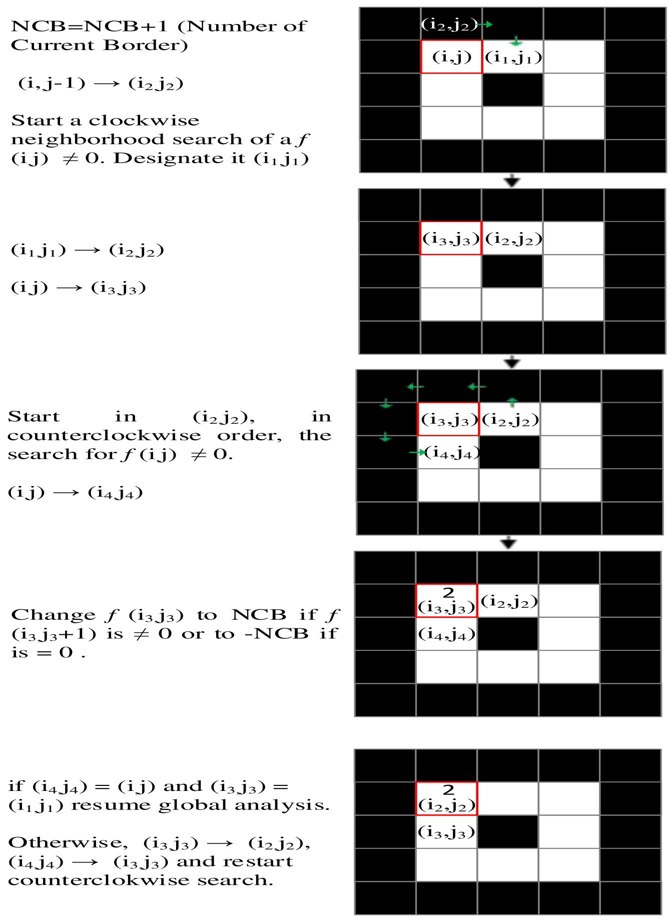


Fig. 5 Following Contours Algorithm

In Fig. 6 are shown the results of applying the contour following algorithm to a roadway image.

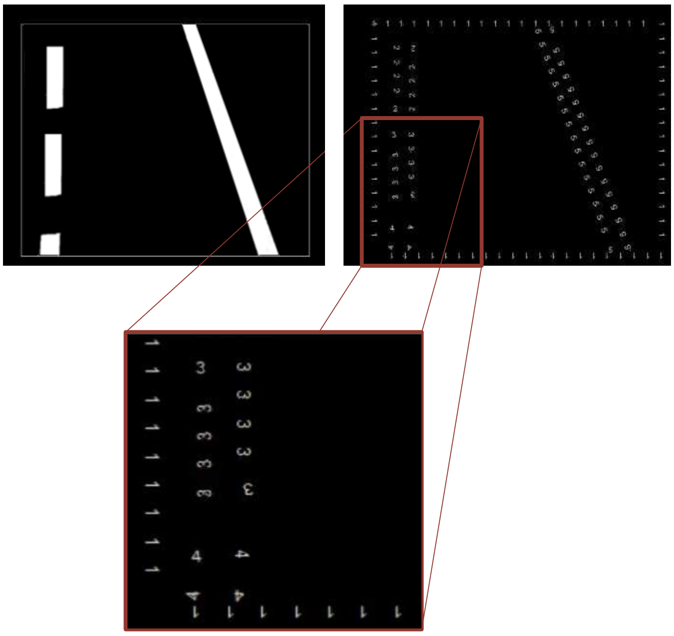


Fig. 6 Contours classification results

Road Lanes Relative Position and Balancing

After detection and classification made by the method described previously, it becomes possible to extract attributes for each road lane, that allow further identification of characteristics such as size or position in the image.

The determination of shapes characteristics are normally based on the theory of moments, statistical properties which describe them. The first significant work in this area was presented in 1962 by Hu [9]. Based on the results of the theory of algebraic invariants, derived seven invariant moments to rotation of 2-D objects, which were used in several works [3].

The moments of order $(p + q)$ of an image with size (m,n) are obtained by the following equation:

$$M_{pq} = \sum_{x=1}^{m}\sum_{y=1}^{n} x^p x^q f(x,y), \qquad p,q = 0,1,2,3,\ldots \tag{12}$$

Where $f(x,y)$ represents the intensity of the pixel (x,y).

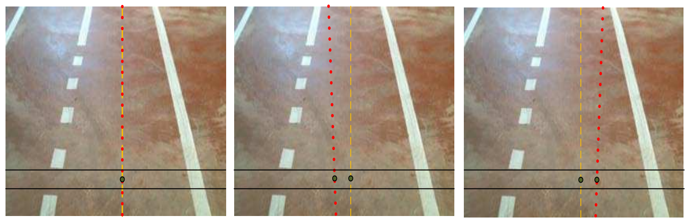
In this work, the shape characteristic important to the control system is the centroid. The coordinates of the centroid may be defined by the relationship between the moments of order 0 and 1 as described in the following two equations:

$$x_c = \frac{\sum_{x=1}^{m}\sum_{y=1}^{n} x f(x,y)}{\sum_{x=1}^{m}\sum_{y=1}^{n} f(x,y)} = \frac{m_{10}}{m_{00}} \tag{13}$$

$$y_c = \frac{\sum_{x=1}^{m}\sum_{y=1}^{n} y f(x,y)}{\sum_{x=1}^{m}\sum_{y=1}^{n} f(x,y)} = \frac{m_{01}}{m_{00}} \tag{14}$$

With the centroid of the road lanes, it becomes possible to determine its location and to assess the robot balancing in the track. This methodology prioritize algorithm simplicity.

When the balancing assumes a positive or negative value, in straight or curve zones, the information that is in fact send to the control system is that the robot is to the right or left of roadway center and is necessary to act in direction (in this case specifically on the speed of the wheels) to align the robot with a new equilibrium position. If the deviation is null, the robot should perform the necessary to keep aligned. Balancing examples are shown in Fig. 7.



a) b) c)

Fig. 7. Balancing - null - a), negative - b) and positive - c) (black lines delimit the interest area.)

When the balancing assumes a positive or negative value, in the information that is in fact send to the control system is that the robot is to the right or left of roadway center and is necessary to act in direction (in this case specifically on the speed of the wheels) to align the robot with a new equilibrium position. If the deviation is null, the robot should perform the necessary to keep aligned.

Independent road lane detection and road width determination allows good results even with partial occluded road lanes.

Control system

As mentioned, it was used a Fuzzy controller [11] to perform the robot motion control.

Fuzzy logic is a technique based on expert knowledge quite effective in mobile robot control [11]. The use of this controller take advantage of its simple implementation and ability to control multiple independent variables (in this case the velocities of the two wheels). It will receive balancing information and react on the driving wheels speed to return to the roadway center.

This controller consists essentially in three steps, Fuzzification; Inference System and Defuzzification.

Fuzzification transform the inputs values (balancing information) in natural language terms with a certain membership degree. For this purpose it was used membership functions.

The inference system is responsible for deducting the reactions (wheels velocities) based on the balancing values and the available knowledge (present in the rule base, in the format "if antecedent then consequent"). During the evaluation of the rules, the input values from the Fuzzification, which corresponds to degrees of membership, are analyzed for the deduction of new allegations (the terms of the rules conclusion).

Defuzzification is the stage where the results of the inference process are converted to concrete actions. In this step the various responses resulting from the rules evaluation were weighted. Depending on this, a numerical value that may be used externally to the controller is assigned to the output (wheels velocities).

IV. RESULTS

The described methodologies were implemented computationally in order to be tested on the mobile platform. The entire implementation was carried out on Windows, using the object-oriented language Python. This work also use several extra libraries like SimpleCV, PySerial and PyFuzzy.

To evaluate the implemented system, was constructed a test course that aims to provide a driving environment similar to a real traffic road, with curve zones, and discontinuous lines.

Presented below are results from tests done to the most important system elements. For each aspect under analysis were performed 15 test laps on the track (Fig. 8).

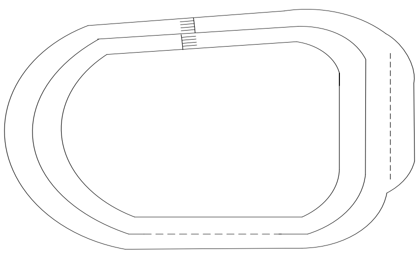


Fig. 8 Schematic representation of the track

Webcam angle influence in system performance

Webcam is positioned at the top of the structure and describes an angle (ϴ) in relation to its support. This angle, influence the capabilities of the entire system. Summarized below are the results of the tests performed at different angles at two different speeds. It should be noted that this test use the interest area position algorithm subsequently analyzed.

Table IV. Influence of webcam angle in system performance

Influence of Webcam Angle in System Performance					
Webcam Angle (ϴ)	*15º*	*30º*	*45º*	*60º*	*75º*
% Course Completion (2 cm/s)	*80 %*	*87 %*	*93 %*	*73 %*	*67 %*
% Course Completion (4 cm/s)	*73 %*	*80 %*	*87 %*	*67 %*	*60 %*

From the above table, it is possible to verify that the angle which led to a higher percentage of laps completed successfully to the course was 45º. With this angle, on average, for two-speeds in test, 90% of test laps were successfully completed.

Benefit of interest area positioning algorithm

The utility of the algorithm responsible for determining the interest area position dependent on the speed, is evaluated by comparing the ability to complete the course conveniently with and without its use.

Table V. Utility of interest area algorithm - course completion

Utility of Interest Area Algorithm - Course Completion (%)				
Speed	*2 cm/s*	*4 cm/s*	*6 cm/s*	*8 cm/s*
Wihout Positioning Algorithm	*87 %*	*73 %*	*60 %*	*53 %*
With Positioning Algorithm	*93 %*	*87 %*	*80 %*	*73 %*

From the previous table, is possible to conclude that for low speeds, the positioning algorithm wasn't very significant. However, with the speed increase, the algorithm inclusion leads to a greater ability to successfully complete the course.

Optimal Threshold automatic determination

In the following figure are shown two sets of images obtained with the implemented algorithm. It is possible to see that despite the original image conditions, the determined threshold allows a fairly good result for the binarization process.

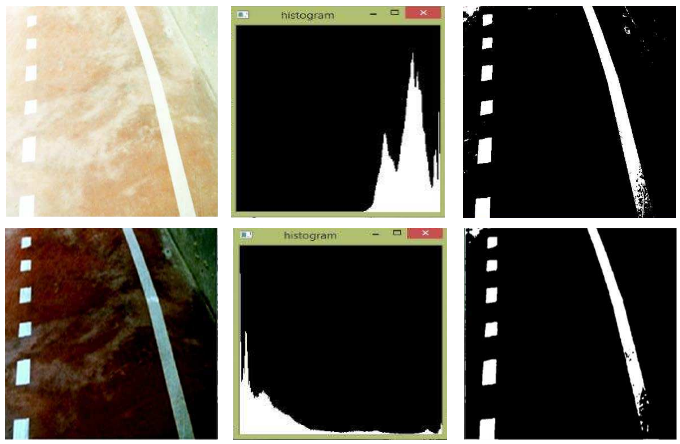


Fig. 9 Automatic Threshold – Top 210, Bottom 111

Global analysis of the image processing

The image processing culminate in the lanes detection. All the previous steps are designed to provide the ideal conditions for the detection algorithm extract the needed information to control the robot.

The fails in detection of one or simultaneously two lanes during the robot movement allows the evaluation of the implemented algorithm robustness.

Table VI. Road lane detection

Road Lane Detection (%)				
Speed	*2 cm/s*	*4 cm/s*	*6 cm/s*	*8 cm/s*
Detection Fail - 1 Lane	*0 %*	*7 %*	*7 %*	*13 %*
Detection Fail - 2 Lane	*0 %*	*0 %*	*7 %*	*7 %*

Robot Movement

Although the previous steps show satisfactory results, the robot ability to follow a certain path, in this case a lane, is conditioned by the Fuzzy controller used and need to be also evaluated. It's his capability and good parameterization that will ensure a functional guidance system.

Therefore, in order to validate the overall system performance, were taken test laps on the track that led to the following:

Table VII. Global efficiency of implemented control system

Global Efficiency of Implemented Control System (%)			
2 cm/s	*4 cm/s*	*6 cm/s*	*8 cm/s*
87 %	*80 %*	*73 %*	*67 %*

The table above summarizes for each speed in test, the percentage of laps successfully completed by the robot.

As expected, the speed increase reduce the system efficiency. During the tests, was seen that the areas most prone to failure during the lane following were curves and zones with discontinuous lanes. Was also verified that lighting conditions and zebra cross presence doesn't significantly affect the results.

V. CONCLUSIONS

The development of an autonomous guidance system is a complex task, which involve several intermediate steps. Achieving good results implies that these steps are effective in the functions that they depend.

The developed methods to process the image and recognize the traffic lanes, proved to be capable of acquire sufficient and appropriate information to guide a robot in a path similar to a roadway. The obtained results are very positive, since the central axis identification were impossible only in 7% of the tests. The automatic interest area positioning and the automatic determination of threshold made an important contribution to the good results achieved.

The control system depends essentially from Fuzzy controller. This controller allows satisfactory results, making the movement of the robot in the lane quite robust. For the higher test speed 8 cm/s the overall efficiency were 67%, which proved the validity of the control rules and parameters used in Fuzzification and Defuzzification. Besides the control ability demonstrated, the implementation simplicity, was another aspect that attested this choice.

Overall, the results obtained in this work show that the methodologies adopted, the robotic structure implemented and the software chosen, can be used to create a mobile robot capable of performing tasks related to autonomous driving in a real roadway.

Despite the positive results, in future work, the Fuzzy controller can be improved and the mechanical structure can be upgraded, for example, with a directional axis. This make it more similar to a car and would allow higher circulation speeds.

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