Detection of Lateral Borders on Unmarked Rural Roads

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***Abstract*— This work presents a method to detect roads in rural conditions, considering gravel or stabilized roads. The main features of this type of ways are based on they do not have lanes and either lateral or central delimitations. This type of road is common in several countries that, for their infrastructure road, still have a large percentage considered as belonging to red earth - without paving or delineating. In order to detect the edges of the paths, this work proposes an analysis strategy based on channel selection on HIS color map representation. The selection automatically allows detecting the channel which brings better information. A convolution filter sequence combined with an adaptive Hough Transform is then applied to detect of curves in the way.**

Keywords—driver assistance; rural roads; image processing

I. Introduction

In Argentina exists approximately 500.000 km of roads, of which 37.800 belong to the national infrastructure network, and 178.000 to the secondary network [1].

TABLE I. ARGENTINIAN ROAD NETWORK

	Km. Linear	Percent
Buenos Aires	18.900	50%
Center	7.560	20%
North	5.292	14%
Mesopotamia	2.268	6%
Cuyo	2.268	6%
South	1.512	4%
Total	**37800**	

A total of 61.000 km of primary and secondary network are pavement, and 37.000 km of the rest have some type of improvement (grave or stabilization). The remaining 117.000 km are dirt roads, as are the vast majority of those forming the tertiary network, which means that Argentina has more than 400.000 km of dirt roads (approximately 80% of total vial network).

TABLE II. LENGTH OF ROUTES BY TYPE.

Type of road	Kms
Asphalt	170.395
Ground	142.610
Concret	83.270
Ripio	40.550
TOTAL	**436.825**

Also, 20.000 km have asphaltic slabs and almost 1.000 km consists of concrete slabs, and 8.000 km with bituminous treatment. From this indicators, can assume that 80% of road network is comprised of dirt roads, gravel or some type of stabilization. This number motivates to analyze and provides solutions for road detection in non-structured roads.

Statistically, in our country 49% of traffic accidents occur in rural areas [2]. Also, the percent of accidents occurring in road types with abnormal conditions (gravel, dirt, wet pavement, etc.) is 12 % [3]. Traffic accidents occupy the 13th place of the causes of mortality in Argentina [4] (2.17% in 2014) involving a total of 7268 fatalities in 2016 [2].

Currently several automotive companies are incorporating the integration of intelligent systems in products of their industry. The solutions try to avoid situations of risk to drivers. Within the capabilities provided includes the lane detection systems. The lane detection refers to the automatic process of locating road limits without knowledge of the road infrastructure. The use of these techniques tries to mitigate the possible risks. It allows detecting closed curves, and presence of obstacles in the same lane of the vehicle. Also, drivers sometimes are not aware of lane changes by distraction or fatigue. In this way, it is important to know the position of the vehicle on the route, and alert the driver to possible danger situations.

Several techniques to lane detection can be applied in well-structured and defined roads, with structure and marks. These techniques are based on this set of assumptions:

- The texture of the road is consistent.
- The lane is well defined.
- The width of the lane is constant.
- The lane signals follow strict rules for appearance or placement.
- The road is a flat surface or follows a strict model of elevation.

Existing algorithms use at least one or more of the above assumptions and this set tend to improvements in overall results. However, these can be missing. The hypothesis of a constant road texture can greatly improve the results of its entire surface. It can be used as additional information to road markings. In situations where road markings are scarce or absent, provides an estimate for vehicle position in the lane.

Also, a constant lane width can improve the detection algorithms, through the fusion of laterals limits.

Road markings are often clear and continuous on a dark surface. It is often assumed that the surface of the road is flat or follows a constant pattern of elevation. However, the assumptions of elevations can lead to an incorrect estimation of the road curvature.

Unstructured paths exist, where there are no obvious lanes or boundaries marks besides. This type of roads is vulnerable to changes in illumination and shadows. Here the road texture will depend on the type of material used for refilling, or in many cases, the existing natural material: earth, clay, gravel, stone, etc.

The road limits usually are determined by the natural accidents of geography, such as rocks, groves, property boundaries, and others. Moreover, the signaling on rural roads is limited, barely with indications of some important geographical accident. Finally, this type of road does not follow any strict elevation model.

According to [5] methods of detection of unstructured roads can be classified into three groups: based on the road model, based on road features and based on previous knowledge acquired through neural networks. The model-based approach assumes a road with regular boundaries and analyzes feature points to determine membership to a predefined model. The road-based method analyzes variations in color and texture to determine road limits. The third group, the detection by using neural networks is based on the detection of the particular route features from a large number of previous samples used as training set of a neuronal system.

The rural roads belong to the group of unstructured roads. These roads were strongly influenced by the rural environment, with strong changes due to illumination (due mainly to the presence of trees), poor definition of lateral boundaries (since road and bank material are usually the same one) and bad morphological features (width discontinuous limits and dependent of terrain). For that reasons, the detection of road boundaries can involve a major effort in terms of algorithms and consequently, processing time.

A set of works treat the detection of limits of lanes in this type of ways. Unfortunately, there is reduced in comparison to detection of lanes and other objects (pedestrians, informational signs) on structured roads.

In [5] a method for road rail detection is presented to be applied complex environment. The method implies a conversion and analysis of the component hue from a HIS color space, to detect the road boundaries.

On the other hand, [6] proposes other algorithm considering initial similarities to the previous. The method involves an image preprocessing stage with a greyscale conversion based on a weighting equation of the RGB components of the original image.

Kong *et al* [7] describes an image analysis using a structured method to determine texture features through a Gabor filter. The startup analysis was intended to be performed on a weighted transformation of the RGB space color components

Another method was proposed in [8], where three main areas are estimated: horizon (in the top of the image), the road area and the laterals. These regions are analyzed in terms of features: image location and intrinsic composition from its color components.

Crisman et al [9] propose a method to navigate in not structured rails based on pattern recognition. This technique uses a pixel grouping according to location and color. The obtained result is contrasted to road shape models to locate the boundaries

Also, other publications in literature performs the road boundaries detection in rural areas using stereoscopic vision, LIDAR [10,11], or the analysis of data collected from a set of sensors[12].

In this paper, an alternative method to detect boundaries in rural roads is proposed. As others methods of literature, the method is based on the information from an image sensor, but incorporate a channel selection stage to determine which color component brings better results.

The section 2 of this work presents the proposed technique, in section 3 the results obtained from the evaluation of the algorithm using real images, and finally section 4 details the conclusions.

II. PROPOSED METHOD

The proposed method is based on a set steps applied sequentially to obtain lateral boundaries (Fig. 1). In the first step, the image is transformed from RGB space to HSV. Second, the histogram of each channel (hue, saturation, value) is determined to detect which color component contains better information about the path. A smooth filter is applied later to reduce imperfections of the edge of the road, in addition to a threshold filter to eliminate the illuminated parts of the image. A Laplacian filter is used to highlight the regions of the road and the edges of the same. The edge detection is done applying Roberts filter. Finally, a Hough-based optimization allows detecting the road boundaries lines.

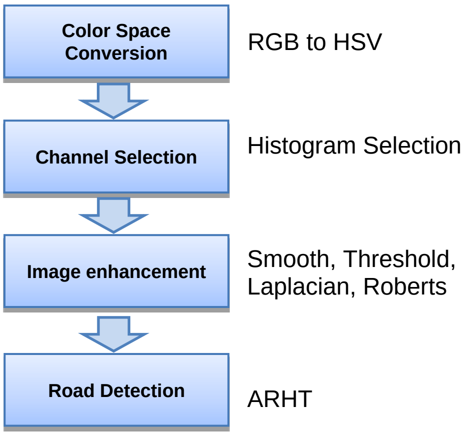


Fig. 1. *Proposed system.*

A. *Color Space Conversion*

The use of a RGB color space does not provide useful information because the three color components are interrelated. A transformation to the HSV space was proposed to solve the inconvenience. In a first approach, the color space map was converted using the standardized conversion equations. The results for three examples roads are shown in figure 2.

The results show that Hue channel (*H*) contains better definition of the path itself with respect to the environment. Other variants of conversion equation were analyzed, in order to improve the results.

$$H = \begin{cases} 0° & ,\Delta = 0 \\ 60°x\left(\frac{G-B}{\Delta} mod\ 6\right) & ,Cmax = R \\ 60°x\left(\frac{B-R}{\Delta} + 2\right) & ,Cmax = G \\ 60°x\left(\frac{R-G}{\Delta} + 4\right) & ,Cmax = B \end{cases} \quad (1)$$

Where *R*, *G*, *B* are normalized; the maximums and minimums value for R, *G* y *B* are defined by *Cmax* and *Cmin*, and Δ represents the difference between *Cmax* and *Cmin*.

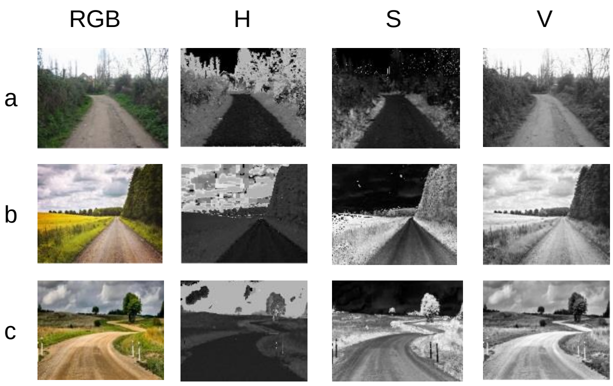


Fig. 2. *Conversion to HSV space map.*

The border processing is carried out applying two convolution filters: Laplacian and Roberts. The Laplacian improves the resulting image, delineating the edges of the image (including the road). After this step, the Roberts filter obtains higher continuity. The Fig. 2 b) and c) presents the application of the filters to an experimental image.

A modification in parameter equations let to obtain better results for hue calculation. Thus, depending on the predominant color in each pixel (R, G, B) the hue is shifted 120, 240 or 360 degrees.

B. *Channel Selection*

The type of terrain, road construction material, surrounding vegetation and so many other factors determine the specific information about the road that will be obtained from components of an HSV color space. Sometimes, the hue channel that provides better information about road limits in a specific environment, but with other conditions leads to use the saturation channel. Also, the intensity channel provides relevant information in extraordinary conditions and the use of this component is uncommon.

On the other hand, a camera located in the front of the vehicle will capture an image that can be subdivided into 4 regions, as is depicted in Figure 3. The region of interest to be analyzed is contained in the lower half of the image, leaving the upper zone relegated to reflect information of the horizon or the distant topography to the vehicle

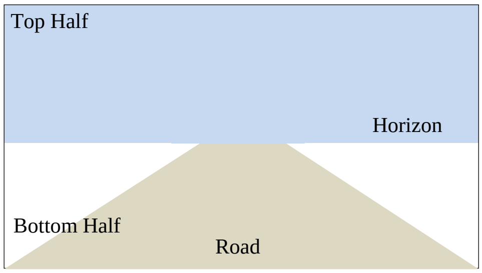


Fig. 3. *Identified regions of interest in a road image.*

A technique based on histograms is proposed. Each histogram is calculated from lower half for each one the three channels. The goal of this stage is determining which of them will contribute to the later steps for boundaries recognition.

The pixel selection is based on the analysis of dark pixels and their frequency (Fig. 4). In this way, the first 40 histogram values will be analyzed to determine the channel that can provide more efficient results. The method proposes the selection based on choosing the histogram containing peaks in the interest region and low frequency in the remaining region.

In the example presented in Figure 5, the histogram for intensity component does not provide relevant information to determining the road boundaries. Therefore, the useful information can be extracted from the hue and saturation channels. In addition, the histogram for hue channel contains a great concentration of dark pixels (1400 pixels approximately, with peaks of 40), while the histogram for saturation channel also contains dark pixels, but with less concentration. In this particular image, is recommendable to use the hue component based on the dispersion curve obtained from histograms analysis.

(a) (b) (c)

(d) (e) (f)

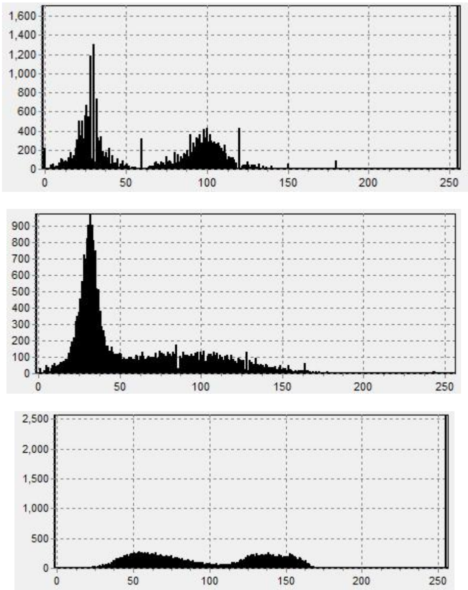
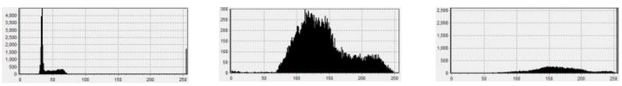


Fig. 4. *Histogram for H, S and V component applied to road 2 a). d) H Histogram (a). e) S Histogram (b) and, f) V Histogram(c).*

C. Image Enhancement

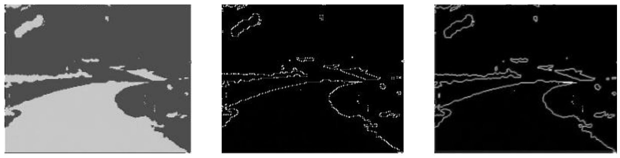
A convolution filter is applied to smooth the image, to eliminate or reduce the noise on road limits. The kernel is formed by unity matrix. An additional threshold eliminates the most illuminated image information leaving only the road profile. Additional regions with a hue value similar to the road may exist as result (Figure 5). These regions are considered as undesirable.

(a) (b) (c)



(d) (e) (f)

Fig. 5. *Smooth (b) and threshold (c) from H component (a) applied en in Fig. 3 c). Histograms for H (d), V (e) and S (f) components*



(a) (b) (c)

Fig. 6. *a) Laplacian Filter. b) Roberts Filter, c) Laplacian and Roberts filters.*

Different Laplacian filter masks were evaluated. The best results were obtained using a contrast kernel for all horizontal, vertical and diagonal neighbors.

$$\begin{matrix} -1 & -1 & -1 \\ -1 & +8 & -1 \\ -1 & -1 & -1 \end{matrix} \quad (2)$$

A Robets filter is applied to the resulting image (Fig. 6 a) from previous step. The resulting image is presented in Fig. 6c, and the kernel coefficients are defined as follows:

$$\begin{bmatrix} p11 & p12 & p13 \\ p21 & p22 & p23 \\ p31 & p32 & p33 \end{bmatrix} \quad (3)$$

$$np22 = \sqrt{(p22 - p33)^2 + (p23 - p32)^2} \quad (4)$$

D. Road detection

An alternative to classical Hough transform (ARHT: Adaptive Random Hough Transform [13]) was used to detect the edges of the road. This improved version allows not only the detection of straight lines (as Hough) from the location of points that meet the equation $y = m.x + n$. The ARHT adapt the search path of new candidate points, for the curves following, according to the equation:

$$|arctg(p0)\text{-}arctg(p1)| < threshold \quad (5)$$

The method evaluates the membership of a new point *p1* to the beam of light of a reference point *p0*. So, it is possible to calculate the curvature parameters *c* and tangent direction *td* as follows:

$$c = \frac{(x_0 - x_1) + f_g(x_1, y_1)(y_1 - origen) - f_g(x_2, y_2)(y_2 - origen)}{2\frac{1}{(y_1 - origen)} - \frac{1}{(y_2 - origen)}} \quad (5)$$

$$td = x_1 - \frac{2c}{(y_1 - origen)} + f_g(x_1, y_1)(y_1 - origen) \quad (6)$$

Where *fg(x,y)* is the pixel intensity value at located in the position *x,y.*

After sampling large numbers of pixels, you must choose the most feasible parameters. The execution of the ARHT algorithm, a lot of candidate points are obtained. Thus, it is required a selection of the more appropriate center and radius that meet the threshold error and contain the most of points.

The results obtained from the algorithm to three road images are presented in figure 7.

(a)

(b)

(c)

Fig. 7. *Adaptive Hough Transform*

III. EXPERIMENTALS RESULTS

The experimental evaluation of the proposed method was based on a set of images captured from different videos. A fixed camera was located in the internal of a vehicle to obtain the videos. The reliability of the results was estimated from an algorithm that averaged the horizontal coordinates of both edges in order to obtain an assumed central trajectory (blue line in Figure 7a). The errors were determined in each analysis by comparison between the trajectory and a central reference (noted in red in Figure 8 a)).

TABLE III. EXPERIMENTAL RESULTS.

Video	Image Number	Hits	Percent of error
1	500	441	88.2
2	500	459	91.8
3	500	410	82.0
4	500	432	86.4
5	500	452	90.4
6	500	444	88.8

The proposed method was evaluated in 3000 images from 7 videos. The set comprises crossings in rural trails with the results shown in Table 3 below. The videos were taken in different climatic conditions (with and without drizzle), at different times of the day (with sun for or against) and with direct or dispersed lighting (with or without grove on the sides of the road).

In the literature related to identify limits in rural roads, results between 85 and 91% are considered acceptable. So, the proposed algorithmic process presents good behavior. Also, the decrease of efficiency in video 3 (82%) was produced by a varied grove surrounding the road. The trees introduced shadows in the road affecting the correct processing (figure 8).

Fig. 8. *Image from video 3 with lateral grove.*

IV. CONCLUSIONS

In this paper, a method of recognition of unmarked rural roads based on image filtering and application of an adaptive Hough transformation was proposed. The image is converted from RGB to HSV, as the first step, and the three components are analyzed separately to decide which provides better information about the road limits (generally the H or the S). The image is then filtered using Laplacian and Roberts filters, and the final detection is made by through Hough transform.

The execution times allow processing of the order of 10 images per second. In this way, the system can bring a response each 1.66 meters, in a vehicle driving at 60 km / h.

The obtained results were acceptable in dry or wet roads, with variations of lighting and type of construction material (clay, gravel, stabilized). The system limitations are subject to ambient (strong rainfall) and construction conditions (the delimitation of the road is not by color but by construction: steep ditch, different height, etc.).

ACKNOWLEDGMENT

This work is partially supported by the SECAT-UNICEN (Project ID: 03/c257), and SID-UNTREF (Project ID: 32/15 273).

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