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ROAD-SIGNS DETECTION AND RECOGNITION IN OMNIDIRECTIONAL IMAGES

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ABSTRACT

This paper describes a computer vision system for automatic traffic road-signs detection and recognition in omnidirectional images. Contrasting conventional cameras, omnidirectional ones can provide a 360 degrees field of view, which is very useful for this kind of applications. The proposed approach consists of three major steps. Firstly, the omnidirectional images are unwrapped into a panoramic form. Then traffic road-signs shapes are detected using Hu moment invariants. Finally, the recognition is performed by measuring the multi-dimensional histogram similarity between detected road signs shapes and images stored in a database representing models of road signaling panels. Experimental results have proved the performance of the proposed approach in real conditions of use.

Keywords: road signs detection, recognition, omnidirectional vision, Hu moment invariants, multidimensional histograms.

INTRODUCTION

Recently, omnidirectional imaging sensors have been used in Intelligent Transport System (ITS) area [1]. It permits to perceive different visual information around the system, covering a 360° degrees field of view. It can provide many information to the drivers about road quality, traffic restrictions, warnings, and possible directions, etc...

Typically, road signs include several properties such us: colors and geometrical shapes. A good traffic sign detection and recognition system must be robust against: lighting changes, partial occlusions, shadows etc…

To identify the road signs in images acquired by conventional cameras, many researchers separate this task in two main steps: detection and recognition. The role of the first stage is to detect areas of images that have appropriate traffic signs shape. Then, recognition stage extracts the information of the detected traffic signs. Several road signs detection methods have been developed and used with success: shape-based methods [2], [3], [4] and [5], color-based segmentation methods [6] and classification methods [7]. However, it is still more difficult to detect and recognize them from images acquired by an omnidirectional camera; due to the special geometrical properties of their forming.

In this work, we propose and implement a real time automatic traffic road-signs detection and recognition algorithm on omnidirectional images. This method is based on the Hu moment invariants and multidimensional histograms.

This paper is organized as follows: section II describes the proposed method for road sign detection and recognition, in section III the implementation strategy is given, section IV presents the obtained results, and section V concludes the paper.

METHODS

The road signs detection and recognition method developed in this work operates in three stages: (1) pre-processing, (2) detection, (3) recognition.

Preprocessing

The goal of the pre-processing stage is to transform the acquired catadioptric image (Fig-1.) onto a panoramic form (Fig 2) using the method described in [8]. To optimize the processing time, we enhanced this method by adopting a lookup table technique (LUT) which replaces the following repetitive unwrapping calculations:

$$\boldsymbol{\rho} = \sqrt{\boldsymbol{x^2 + y^2}} \quad (1)$$

$$\boldsymbol{\theta} = \boldsymbol{arctan(x/y)} \quad (2)$$

Where ρ and θ are the polar coordinates of each omnidirectional image pixel. Table 1 shows the processing time of the unwrapping process.

Tableau-1. Different resolution of image and execution time

Input image resolution	Scaling factors (α, β)	Output image resolution	Execution time without LUT (ms)	Execution time with LUT (ms)
64X64	(1, 0.5)	17X100	0,53	0,16
128X128	(1, 0.5)	35X204	2,08	0,64
256X256	(1, 0.5)	67X409	7, 57	2,58
473X482	(1, 0.5)	130X769	24.47	7,97
1683X1689	(1, 0.5)	669X2642	308,80	102,96

Where α and β are scaling factors acting on the resolution and the ratio of the output image.
$\alpha, \beta \in [\,0,1\,]$

It can be seen that the use of the lookup table optimizes the unwrapping process time significantly.

The figure 2 shows a panoramic image. The image is filtered with a 3 by 3 median filter and converted from RGB to grayscale. After that, the scene object edges are detected using canny algorithm.

After this pre-processing step, we obtain an image which contains edges of the road scene objects. This image is swiped, each edge of the image is extracted and the similarity rate comparing each one to the reference shapes edges calculated using Hu moment invariants.

Figure-1. Omnidirectional image

Figure-2. A panoramic image obtained after unwrapping

Detection

The detection method is based on similarity measure using Hu moment invariants. This similarity is calculated by comparing the detected edges from the acquired images to the reference edges of shapes that we are interesting to find, such as a triangle, a circle, or a square (Fig-3).

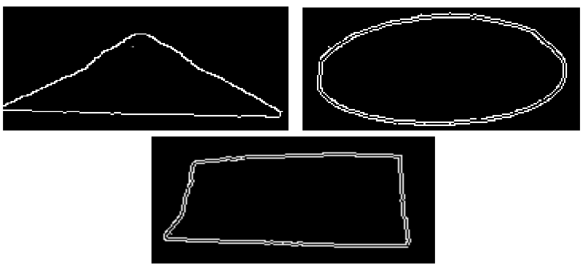

Figure-3. Reference shapes edges.

Invariant moments

Moments and functions of moments have been employed as pattern features in several applications, [9] and [10]. The most famous moments integrate geometric moments [11], Zernike moments [12], rotational moments [13], and complex moments [14]. The moment of an image describe the information about its centroid, intensity, and orientation. They are defined as:

$$M_{pq} = \int_{-\infty}^{\infty}\int_{-\infty}^{\infty} x^p y^q\, f(x,y)dxdy \qquad (3)$$

Where M_{pq} is the $(p+q)^{th}$ order moment of the continuous image function $f(x,y)$. For digital images the integrals shall be replaced by summations and M_{pq} becomes:

$$M_{pq} = \sum_x \sum_y x^p y^q f(x,y) \qquad (4)$$

With $p,q = 0,1,2,\ldots$

We notice that the moments in (4) can be variant when $f(x,y)$ changes by translation, rotation or scaling. The invariant features may be attained by using central moments, which are defined as follows:

$$\mu_{pq} = \int_{-\infty}^{\infty}\int_{-\infty}^{\infty}(x-\bar{x})^p(y-\bar{y})^q\, f(x,y)dxdy \qquad (5)$$

Where:

$$\bar{x} = \frac{M_{10}}{M_{00}} \quad \bar{y} = \frac{M_{01}}{M_{00}}$$

For digital images (5) becomes:

$$\mu_{pq} = \sum_x \sum_y (x-\bar{x})^p(y-\bar{y})^q f(x,y) \qquad (6)$$

The pixel point $(\bar{x},\bar{y})$ are the centroid of the image $f(x,y)$. The centroid moments μ_{pq} computed using the centroid of the image $f(x,y)$ is equivalent to M_{pq} whose center has been shifted to centroid of the image. Therefore, the central moments are invariant to image translations. Scale invariance can be achieved by normalization. The normalized central moments are defined as follows:

$$n_{pq} = \frac{\mu_{pq}}{\mu_{00}^{(1+\frac{p+q}{2})}} \qquad (7)$$

Where n_{pq} is the scale invariant moments, $p+q \geq 2$ can be constructed to be invariant to both translation and changes in by dividing the corresponding central moment by the properly scaled $(00)^{th}$ moment.

In this paper we used seven nonlinear Hu moment (Tab-2) introduced by Hu [15] for its skills to be invariant under translation, changes scale, and also rotation. These seven moment invariants were used in a certain number of pattern recognition issues [16], [17] and [18].

The first one h_1 is analogous to the moment of inertia around the image's centroid, where the pixels intensities are analogous to physical density. The last one h_7 is skew invariant, which enables it to distinguish mirror images of otherwise identical images.

To compute the similarity between the edges located in the road scene and the edges of reference shape, we use following formula based on seven Hu moment invariants:

$$T_{taux1} = max_{i=1,\ldots,7} \frac{|m_i^A - m_i^B|}{|m_i^A|} \qquad (8)$$

Where:

$$m_i^A = sign(h_i^A).\, log h_i^A$$
$$m_i^B = sign(h_i^B).\, log h_i^B$$

If T_{taux1} is lower than a fixed threshold, the coordinates of the selected edge are saved, then we extract the selected image part from the filtered image and we save it to be re-used in the recognition step.

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Tableau-2. Seven Hu moment invariants introduced by Hu [15].

h_1	$n_{20} + n_{02}$
h_2	$(n_{20} - n_{02})^2 + 4n_{11}{}^2$
h_3	$(n_{30} - 3n_{12})^2 + (3n_{21} - n_{03})^2$
h_4	$(n_{30} + n_{12})^2 + (n_{21} + n_{03})^2$
h_5	$(n_{30} - 3n_{12})(n_{30} + n_{12})[(n_{30} + n_{12})^2 - 3(n_{21} + n_{03})^2] + (3n_{21} - n_{03})(n_{21} + n_{03})[3(n_{30} + n_{12})^2 - (n_{21} + n_{03})^2]$
h_6	$(n_{20} - n_{02})[(n_{30} + n_{12})^2 - (n_{21} + n_{03})^2] + 4n_{11}(n_{30} + n_{12})(n_{21} + n_{03})$
h_7	$(3n_{21} - n_{03})(n_{30} + n_{12})[(n_{30} + n_{12})^2 - 3(n_{21} + n_{03})^2] - (n_{30} - 3n_{12})(n_{21} + n_{03})[3(n_{30} + n_{12})^2 - (n_{21} - n_{03})^2]$

Recognition

The recognition method is based on measuring the similarity between the detected image and images located in a database using multidimensional histograms.

Color histograms are largely used for content-based image retrieval [19] and [20] because they are simple to compute, and despite their simplicity, they have interesting properties. They are invariant to the rotation and translation of objects in the image. Additionally, color histograms are robust against occlusion and changes in camera viewpoint. In the color histogram approach of Swain and Ballard [21] an object in an image is identified by matching a color histogram from a region of the image with a color histogram from a sample of the object. Their technique has been shown to be insensitive to changes in the object's orientation and changes of the scale of the object. The focus of our work has been to develop a robust technique using the multidimensional histogram to recognize the road signs detected in the first step. For this, four databases are created to compare the detected signs with the signs located database (Fig 4, 5 and 6).

Figure-4. Square panels

Figure-5. Circular panels

Figure-6. Triangular panels

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The comparison is performed using the correlation distance:

$$D_{(H_1,H_2)} = \frac{\sum_I (H_1(I) - \tilde{H}_1)(H_2(I) - \tilde{H}_2)}{\sqrt{\sum_I (H_1(I) - \tilde{H}_1)^2 \sum_I (H_1(I) - \tilde{H}_1)^2}} \quad (9)$$

Where

$$\widetilde{H_k} = \frac{1}{N}\sum_I H_k(I)$$

N is a total number of histogram bins.

A high score represents a better match than a low score. A perfect match is 1 and a maximal mismatch is –1; a value of 0 indicates no correlation.

EVALUATION STRATEGY

The algorithm is implemented using the Intel ® Open Source Computer Vision Opencv 2.4.8. The database traffic sign image consists of 20 images with are containing three different traffic sign shapes (Fig 4, 5 and 6).

Experiments

To evaluate the performance of the method, five groups are considered and defined:

1 = DR: the number of Detected and recognized panels.
-1 = DU: the number of detected and unrecognized
0 = ND: the number of not detected panels.
-2 = DF: the number of detected and false recognized ones.
-3 = FD: the number of false detection.
Right rate: rate of good recognition.
False rate: rate of unrecognized panels.

Table 3 shows the values of different rates of road signs detection and recognition in real time for different color spaces and histogram dimensions.

Tableau-3. Performance statistics

Color space	DR	DU	ND	DF	FD	Right Rate	False Rate
RGB 3D	11	1	0	7	1	55%	45%
HSV 3D	11	0	0	7	2	55%	45%
LAB 3D	10	0	0	8	2	50%	50%
YcbYc 3D	10	0	0	8	2	50%	50%
HS 2D	**14**	**0**	**0**	**4**	**2**	**70%**	**30%**
BG 2D	13	0	0	5	2	65%	45%
La 2D	12	0	0	6	2	60%	40%
Ab	12	0	0	6	2	60%	40%
Ycr 2D	10	0	0	8	2	50%	50%
Ycb 2D	11	0	0	7	2	55%	45%
CbCr	11	0	0	7	2	55%	45%

The empirical study showed that the margin for error detection algorithm often tends to 0. Indeed, the choice of reference edges plays an important role in the calculation of the similarity.

The similarity measure between two images by calculating the multidimensional histogram combines two key features of the image, which are the number of pixels and their color. In use of the histogram in the RGB space 2D, some combination of colors can represent road signs better than other ones, such that the combination BG which could reach recognition rate of 65 %. The histogram in the 3D RGB space is more sensitive to variations of the illumination. On the other hand, the separation of luminance and chrominance information can represent colors more independently of lightening conditions. It is found that the combination of 2D HS histogram representing the hue and saturation of each color despite of the brightness gives the best results. The 3D HSV histogram that includes information about the pixel brightness, naturally offers performances that seem less satisfactory. In the case of Lab and YCbCr space, the color chrominance is misrepresented by their components, when compared to the HSV color space.

CONCLUSIONS

In this paper, we described a new approach for automatic road signs detection and recognition in real time in omnidirectional images. The traffic road signs are detected using Hu moment invariants. The recognition stage is achieved using multidimensional Histograms. The evaluation study showed that the Hu moment invariants are robust as a detection method. The 2D HS histogram seems to be a good color space for road sign recognition.
As future work, we plan to detect and recognize road signs from omnidirectional images directly, without the unwrapping process.

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