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An Approach for Traffic Road-Signs Detection in Omnidirectional Images

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Abstract- This paper presents an approach for road sign shapes detection in omnidirectional images. The spherical mirror used to acquire omnidirectional images provides a non-uniform resolution over all the image which cause some geometric distortions. Consequently, the real road sign shapes become distorted and so, the detection is more complicated. This work deals with this issue and proposes a detection method based on Hu invariant moments. For that, a database is constructed, for each road sign shape extracted from its omnidirectional image along radial direction. Then, the detection is achieved by classification method based on searching the best interval of discriminant element from the seven Hu invariant moments that could distinguish between the shapes. Experimental results demonstrate the feasibility of the proposed approach relatively in real time.
Keywords – Road-sign, omnidirectional images, invariant moments.

I. INTRODUCTION

Road sign detection is a fundamental and significant topic in smart vehicle and computer vision. It consists on finding the regions of interest of the images that contain road signs. Several techniques have been developed and used to detect traffic signs in conventional images ([1], [2], [3], [4] and [5]). Nevertheless, their detection still more difficult in images acquired by an omnidirectional camera due to non-uniform resolution over all the image caused by the mirror's geometry.

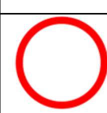
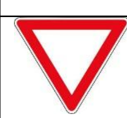
Recently, omnidirectional imaging sensors have received a great interest in traffic systems area [6]. It can provide an image of the surrounding scene with a 360 degrees field of view ([7], [8], [9] and [10]). A few works have treated the problem of detecting traffic signs in these images. The first work of detecting and recognizing road signs in omnidirectional images was proposed by [11], in which the obtained images have been unwrapped to panoramic images before the detection process, the goal was minimize the distortion caused by the mirror geometry. In this approach, we propose and implement a real time outdoor automatic traffic road signs detection algorithm. This method is based on the Hu moment invariants. The benefit of this paper is twofold. First, a general method to divide the omnidirectional image to zone depending of the distortion provided by the mirror is presented. Secondly, we show a method for finding the best interval of discriminant elements from the seven Hu invariant moment to distinguish between shapes representing road signs (triangle, square, circle, and octagon).

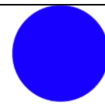
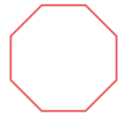
This paper is organized as follows: section III describes the proposed method for road sign detection, in section IV the implementation strategy is given with the obtained results, and section V concludes the paper.

II. REQUIREMENTS

Traffic signs come in many shapes, size, and colors. Table 1 illustrate the meanings of various colors and shapes for signs used in this work.

Table -1 Different type of road signs and their meaning

Meaning	Shape	Color	Template
Prohibition	Circle	Red	
Danger	Triangle	Red	

Recommendation	Square	Blue	
Obligation	Circle	Blue	
Stop	Octagonal	Red	
Guidance signs	Rectangle	Blue	
End of prohibition	Circle	White	
Construction	Circle/Triangle	Yellow	

From Mathematicians side, moments are the "projections" of a function onto a polynomial basis (similar, to Fourier transform that is a projection onto harmonic functions basis). The polynomial basis $p_{kij} = x^k y^j$ was chosen to represent geometric Moments. A two dimensional (p+q) - th order general geometric moment of an M X N image is defined as:

$$M_{pq} = \sum_{x=0}^{M-1}\sum_{y=0}^{N-1} x^p y^q f(x,y)dxdy \quad (1)$$

Pattern recognition using moment invariants was originaly investigated by Hu [13]. Hu defined a set of seven values, invariant to object scale, position and rotation. Those values are computed by normalizing central moments through the third order. In function of the central moments, the seven Hu moments are given as:

$$\mathrm{Hu}_1 \quad n_{20} + n_{02} \quad (2)$$

$$\mathrm{Hu}_2 \quad (n_{20} - n_{02})^2 + 4n_{11}{}^2 \quad (3)$$

$$\mathrm{Hu}_3 \quad (n_{30} - 3n_{12})^2 + (3n_{21} - n_{03})^2 \quad (4)$$

$$\mathrm{Hu}_4 \quad (n_{30} + n_{12})^2 + (n_{21} + n_{03})_2 \quad (5)$$

$$\mathrm{Hu}_5 \quad (n_{30} - 3n_{12})(n_{30} + n_{12})[(n_{30} + n_{12})^2 - 3(n_{21} + n_{03})^2] + (3n_{21} - n_{03})(n_{21} + n_{03})[3(n_{30} + n_{12})^2 - (n_{21} + n_{03})^2] \quad (6)$$

$$\mathrm{Hu}_6 \quad (n_{20} - n_{02})[(n_{30} + n_{12})^2 - (n_{21} + n_{03})^2] + 4n_{11}(n_{30} + n_{12})(n_{21} + n_{03}) \quad (7)$$

$$\mathrm{Hu}_7 \quad (3n_{21} - n_{03})(n_{30} + n_{12})[(n_{30} + n_{12})^2 - 3(n_{21} + n_{03})^2] - (n_{30} - 3n_{12})(n_{21} + n_{03})[3(n_{30} + n_{12})^2 - (n_{21} - n_{03})^2] \quad (8)$$

The distortions provided by the mirror´s geometry used in catadioptric camera (Fig. 1 and 2) leads to a non-uniform resolution all over the image (the image resolution is lower at the center than at the periphery). The pixel coordinates (x0; y0) have to be centered:

$$x = x' - x_c \quad (9)$$

$$y = y' - x_c \tag{10}$$

Thus they can be transformed to polar cordinates ($\rho;\theta$), which are given by the equations 4.

$$\rho = \sqrt{x^2 + y^2} \tag{11}$$

$$\theta = arctan(x/y) \tag{12}$$

Given that the resolution is not uniform over the sphere which changes the geometry of the visual information in the catadioptric images, a database is set, for each road sign shape extracted from its omnidirectional image along radial direction. This database contains different values of Hu invariant moments for each shape along radial direction in different distance from the catadioptric camera.

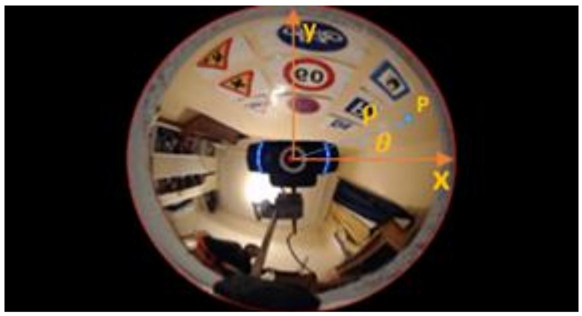


Figure 1. Polar coordinates in Catadioptric image

III. THE PROPOSED APPROACH

3.1 Pre-processing

The second part of our work is to find the elements from the set of Hu invariants witch give the most discriminating results to distinguish between each form of the panels. We use the values of the seven Hu moments calculated in the first part of the work for each form in different distance from the catadioptric camera. We obtain:

Figure 2. Example of the measurement performed for a Square panel to compute its Hu invariant moment vector in different distances and heights from the catadioptric camera

$$T_{Hu_{i=1,\dots,7}} = \{Hu_{i_{j=1,\dots m}}\} \tag{13}$$

$$C_{Hu_{i=1,\dots,7}} = \{Hu_{i_{j=1,\dots n}}\} \tag{14}$$

$$Cr_{Hu_{i=1,\dots,7}} = \{Hu_{i_{j=1,\dots k}}\} \tag{15}$$

$$O_{Hu_{i=1,\dots,7}} = \{Hu_{i_{j=1,\dots p}}\} \tag{16}$$

Where m; n; k; p are the number of samples for each form.
We apply our algorithm to find the optimal interval characterizing each form. We calculate the maximum and minimum value of every Hu component of shape. We obtain:

$$T_{min}\{H_{ui=0,\dots,7_{min}}\} \leq \text{Triangle} \leq T_{max}\{H_{ui=0,\dots,7_{max}}\} \tag{17}$$

$$C_{min}\{H_{ui=0,\dots,7_{min}}\} \leq \text{Cercle} \quad \leq C_{max}\{H_{ui=0,\dots,7_{max}}\} \tag{18}$$

$$Ca_{min}\{H_{ui=0,\dots,7_{min}}\} \leq \text{Square} \leq Ca_{max}\{H_{ui=0,\dots,7_{max}}\} \tag{19}$$

$$O_{min}\{H_{ui=0,\dots,7_{min}}\} \leq \text{Octogonal} \leq O_{max}\{H_{ui=0,\dots,7_{max}}\} \tag{20}$$

We search the element from the seven Hu elements of the vector who gives the best discrimination results for the shapes. We have four sets: $T_{Hu_{i=1,\dots,7}}$, $C_{Hu_{i=1,\dots,7}}$, $Cr_{Hu_{i=1,\dots,7}}$ and $O_{Hu_{i=1,\dots,7}}$.
We calculate the number of the values includeded in other sets for the same element of Hu.
The element who gives the lower number is considered as the best discriminant element.
Let us have a set of the shapes P = {Triangle, Circle, Square, Octagon} such that each shape have seven sets. Each sets represent the value of Hu invariant for each shape.
The best discriminant element of the seven Hu invariant moments who can distinguish the four shapes of roads sign can be chosen as following the Algorithm 1. As we can see from Figure 3 the Hu invariant moments can distinguish between triangle and others shapes using Hu3. For square we considered that Hu4 and Hu5 are the best element for having discrimination between square and other shapes. However, neither one of Hu invariant element can distinguish alone between circle and octagon but a combination of Hu1, Hu2 and Hu6 for a maximum distinction.

$Set\ M = \{M_1, M_2, M_3, M_4, M_5, M_6, M_7\}$;
$P = \{P_1(M_n),\ P_2(M_n),\ P_3(M_n),\ P_4(M_n)\}$;
for $F\ in\ P$ **do**
  for $i = 1..7$ **do**
    $C_i \leftarrow \sum_{j=1}^{4} \delta(F(M_i), P_j(M_i))$;   `// ` $\delta(a,b)$`:Kronecker delta equals 1 if a=b and 0 if not`
  end
  The best discriminant for F is $min(C_1, C_2, ..., C_7)$;
end
for each form the best representing interval is: $\neg(P_i(M_j) \cap P_i(M_k))$, $k \neq j$;

Algorithm 1: Intervals determination algorithm

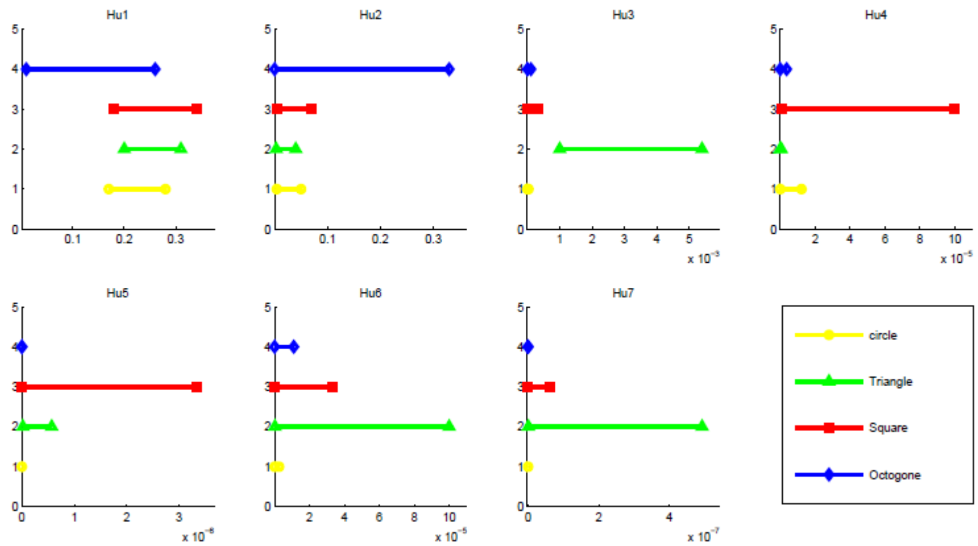


Figure 3. Hu intervals for the studied shapes

IV. EXPERIMENT AND RESULTS

In this section, we demonstrate the feasibility of the proposed method. A catadioptric camera was mounted on the vehicle. While moving at a speed of 25-35 km/h, the mounted catadioptric camera was acquiring at a rate of 17fps, a total of 97 panels were installed along the path. Table 2 shows the results of this outdoor experiment.

Table -2 Shapes Detection Summary

Shapes	Number	Correct detection	non detected	Confusion	Accuracy %
Circle	52	37	10	5	71%
Square and Rectangle	20	15	3	2	75%
Triangle	17	9	8	0	52%
Octagon	8	2	0	6	25%

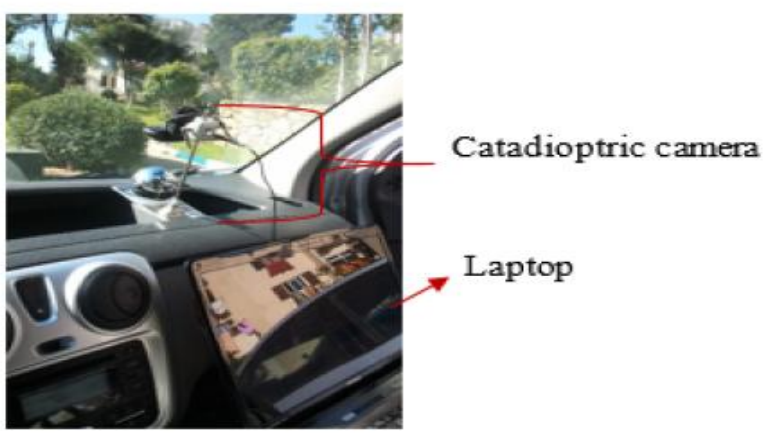


Figure 4. Catdioptric camera and laptop used in this work

We got a detection ratio of 71% for circular panels with 10 undetected and five panels detected with confusion with another form (octagonal or square). In the case of square panels we had a detection ratio of 75% with just three panels detected and three panels detected with confusion. In the case of triangular panels we had a detection rate of

52%, although this rate is not very important, we see that the rate of confusion is zero. Finally, we have achieved a detection ratio very low, which is 25% for the octagon panels.

V. CONCLUSIONS

We have developed a new approach for traffic sign detection, using an omnidirectional camera. The detection was performed by analyzing the Hu moments. The results obtained from the outdoor experiment were very satisfying.
We have proven in our paper that there is an interval that we have non-confusion between the triangular panels and other forms of road signs using Hu3, which explains the level of non-confusion detection. In the case of square panels we also found an interval that allows us to have the maximum discrimination between the square and the other two forms panels using Hu4 and H5. When differentiating between the circle and the octagon the best method was to use Hu1, Hu2 and Hu6.

VI. REFERENCES

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