



# Invariant recognition of rectangular biscuits through an algorithm operating exclusively in hough space. Flawed pieces detection

Javier Montenegro J<sup>a\*</sup>

<sup>a</sup>Virtual Dynamics/Software: Science & Engineering, Calle 14-572, Las Magnolias, Surco, Lima 33, Perú

---

## Abstract

An Algorithm based on the polar Hough Transform has been developed so as to carry out rotation, translation and size-scaling invariant pattern recognition. The algorithm exploits the fundamental properties of the HT and all the required operations take place strictly in Hough space. The developed system has been successfully applied to the recognition of biscuits in the form of rectangular crackers, including flawed pieces, which were easily discriminated against by the algorithm. The results suggest the possibility of an industrial application of this algorithm particularly in industrial quality control. © 2002 CSI. All rights reserved

**Keywords:** Cybernetic Vision; Artificial Intelligence; Computational Vision; Invariant pattern recognition; Invariant shape classification; Polar Hough transform; Biscuit Recognition; Flawed Biscuits Detection.

---

## Resumen

Con la finalidad de ejecutar reconocimiento invariante (rotación, traslación, cambio de escala) de patrones se ha desarrollado un algoritmo basado en la Transformada Polar de Hough, TH. El algoritmo explota las propiedades fundamentales de la TH y además todas las operaciones se llevan a cabo estrictamente en el espacio de Hough. El sistema desarrollado ha sido exitosamente aplicado al reconocimiento de galletas de forma rectangular, incluyendo piezas falladas, las cuales fueron fácilmente detectadas. Los resultados sugieren el uso del algoritmo en la industria, particularmente en control de calidad. © 2002 CSI. Todos los derechos reservados

**Palabras clave:** Visión Cibemética; Inteligencia Artificial; Visión Computacional; Reconocimiento de Patrones; Clasificación Invariante de formas; Transformada Polar de Hough; Reconocimiento de Galletas; Detección de Galletas Falladas.

---

## 1. Introduction

The Hough transform [1-4], HT, is a distortion and noise tolerant technique that maps image-space points into sinusoidal curves in a parameter or Accumulator space. In this work the Polar, also known as Normal Hough Transform is used, this maps image-space points of coordinates  $(x, y)$  into a parametric accumulator space  $(\rho, \theta)$  by means of

$$\rho = x \cos \theta + y \sin \theta$$

In this way, any point in a binary image is mapped into a sinusoidal in the parameter (accumulator) space. The main feature of the HT is that the  $N$  sinusoidals corresponding to a set of  $N$  collinear points  $(x_i, y_i)$  meet at a point  $(\rho_0, \theta_0)$  in accumulator space, the coordinates  $\rho_0$  and  $\theta_0$  characterizing the original straight line in the image. The counting stored in every cell of the accumulator corresponds to the number of points that are contained in

---

\* Corresponding author. E-mail: VirtualDynamicsSoft@yahoo.com

the original line. Due to spatial discretization, lines may be split amongst neighbouring cells.

The Hough transform properties exploited in this work are:

- If a line is rotated by  $\alpha_0$  degrees in image space, then its associated peak in the accumulator is shifted  $\alpha_0$  degrees along the  $\theta$  axis.
- When an object is size-scaled in image-space, only vertical shifts of its associated peaks in the accumulator take place.

The problem of invariant pattern recognition in Hough space has already been addressed by Krishnapuram and Casasent [5], and by Sinha et al [6], none of these two works including the treatment of size-scaling. Authors in references (5) and (6) use convolution in  $\theta$ -space to achieve the rotational registration between sample objects and the templates, an additional processing is then necessary to determine the translational correspondence.

The computational system developed for this work is based on an algorithm that has the following advantages with respect to the methods above mentioned:

- A solution to the problem of object size-scaling is introduced.
- There is no need to place the templates in any particular position or orientation, they are simply thrown into the image-space.
- The object to be recognized is rotated and translated only once in accumulator space, then a comparison with the stored templates is carried out. This represents a substantial improvement respectively to the many comparisons implied by the methods used in references (5) and (6).
- The counting stored in the accumulator cells is also used as an evidence of pattern matching in the present work.

## 2. The strategy of the algorithm

The strategy adopted by the author of the present work to achieve geometric transformation invariant object recognition consists of a basic algorithm that is applied equally to training and recognition stages. After Hough transforming the image-space, a set of operations and transformations is carried out in the accumulator, so that "the object" (the Hough space features associated to the object) is taken to a pre-defined standard position and size in the Hough space, then a characteristic vector is extracted. The use of a pre-defined standard position in Hough space along with Distance-Discriminator Neural Neurons to achieve invariant pattern recognition has been addressed by Montenegro et al [7].

At recognition time, the characteristic vectors  $T$  of template objects previously extracted at the training stage are compared with the vector  $S$  of the sample object to be recognized.

The distance between the template and sample vector gives the corresponding likeliness degree. If several objects appear simultaneously in image-space a pre-processing is necessary to single out individual objects by some of the broadly known labeling [8] techniques.

## 3. Achieving invariance in parameter space

During Training or Recognition stages the object is simply thrown to image-space, in no particular position or orientation. Large instances of the training object should be however preferred for the sake of improved accuracy.

### 3.1. The training stage

Every object is presented only once to the system. Then a set of steps so as to place the object in a predefined standard position take place. Finally the template vector  $T$  is extracted, this stores information about the values of  $\rho$ ,  $\theta$ , and corresponding votation.

### 3.2. Recognition stage

In this stage the same steps carried-out at the training stage are performed, now however a sample-vector  $S$  is created with the corresponding values of  $\rho$ ,  $\theta$ , and votation. Once template  $T$  and sample  $S$  vectors have been extracted, the Euclidean distance between the  $T$ - $S$  pairs is computed.

## 4. Results

The performance evaluation of the algorithm used in this research has been already assessed with computer-synthesized objects, the results showing a very good performance of the algorithm [10,11,12]

The experiment being reported here has been performed using real-life objects, specifically rectangular (biscuits) crackers, whose photographs showing every one of them in different positions, orientations and sizes, were scanned and stored in 128 x 128 pixel binary images, see fig. (1).

Table-1 displays the Similitude Degrees between the 16 rectangular crackers and the five out of them used as templates, one in every case. The names of the objects have the form  $srkb##$ , where  $##$  ranges from 01 to 16.

The top row in table-1 shows the names of the objects used as templates. The first column on the left side shows the names of the samples. The numerical values are the similitude degrees pertaining to each Template - Sample pair. The experiment included four flawed objects, these have one broken corner, and they are identified as srkb08, 09, 12 and 13. Obviously flawed objects are never used as templates. The similitude degrees corresponding to the flawed objects are null because before computing the T-S distance, the program compares the number of object features in T and in S, if these are different no computation is made because it corresponds to objects with different number of sides and the T-S similitude degree must be null. This is precisely the case with the flawed objects, the broken corner introduces an additional peak in the accumulator.

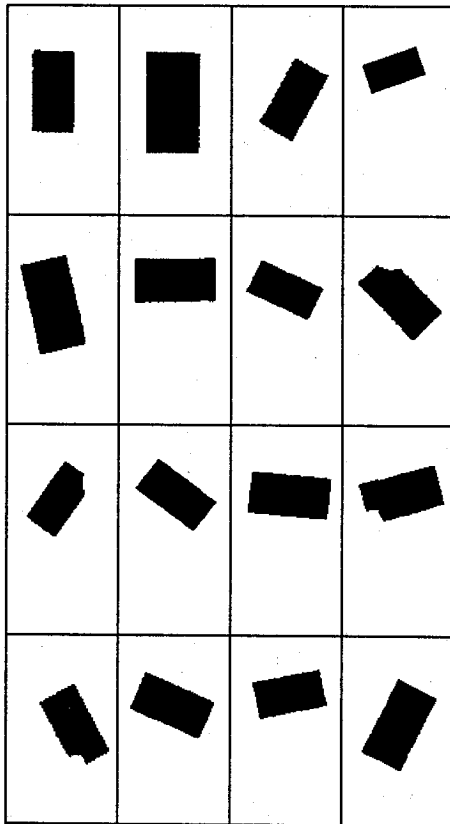


Figure 1.- The 16 photographs of rectangular crackers used in the experiment. Photos Id-numbers go from top to bottom and from left to right. Flawed pieces appear in photos 08, 09, 12 and 13.

It can be seen in table-1, that when a given sample is also being used as a template, the resulting similitude degree is 1.00 as it should be because in these cases Template vector T and Sample vector S are equal. Also it

may be observed that for instance the similitude degree of template srkb01 and sample srkb16 is the same as that corresponding to template srkb16 and sample srkb01, the same situation arises with other objects used in a moment as a template and in another moment as a sample.

Table 1. The top row shows the objects used as templates. The first column on the left side shows the samples. Flawed objects: srkb08, 09, 12, and 13.

Normalized Similitude degrees for 16 rectangular crackers					
	srkb01	srkb16	srkb05	srkb10	srkb07
srkb01	1.000	0.998	0.996	0.995	0.996
srkb02	0.995	0.991	0.993	0.995	0.993
srkb03	0.990	0.992	0.992	0.992	0.991
srkb04	0.994	0.993	0.993	0.994	0.992
srkb05	0.996	0.989	1.0	0.993	0.996
srkb06	0.992	0.989	0.994	0.992	0.993
srkb07	0.996	0.987	0.996	0.996	1.0
srkb08	0.0	0.0	0.0	0.0	0.0
srkb09	0.0	0.0	0.0	0.0	0.0
srkb10	0.995	0.998	0.993	1.0	0.996
srkb11	0.997	0.988	0.996	0.994	0.996
srkb12	0.0	0.0	0.0	0.0	0.0
srkb13	0.0	0.0	0.0	0.0	0.0
srkb14	0.991	0.993	0.992	0.992	0.991
srkb15	0.991	0.988	0.993	0.991	0.992
srkb16	0.998	1.0	0.989	0.988	0.987

## 5. Conclusions

The problem of rotation, translation and size-scaling invariant pattern recognition has been treated and an algorithm based on the fundamental properties of the HT has been developed and successfully applied to the invariant recognition of rectangular (biscuits) crackers.

An important point to mention is that in the method that has been developed the objects are subject to translation, rotation and size-scaling strictly in the Hough space, and

only once, thus saving computing time and reducing the computational complexity of the algorithm.

When dealing with rectangular crackers the program successfully identifies flawless pieces, yielding a good similitude degree between template pattern and samples. The system also discriminates against flawed pieces, so it may be applied to industrial quality control.

#### Acknowledgement

The author would like to express his gratitude to Miss Marlene Gonzalez Reyes for the cracker photographs and related work.

#### 6. References

- [1]. J. Illingworth. and J. Kittler. A survey of the Hough transform. CVGIP, vol , 44, pags 87-116, (1988).
- [2]. P.V.C Hough. A method and means for recognizing complex patterns. U.S. patent 3.069.654, (1962).
- [3]. R. O. Duda. and P.E. Hart. Use of the Hough transform to detect lines and curves in pictures. Communications of the ACM, Vol 15, No 1, 11-15, (Jan 72)
- [4]. R Gonzalez. and R. E. Woods. Digital image processing Addison-Wesley Publishing, (1992).
- [5]. R. Krishnapuram. and D. Casasent. Hough space transformations for discrimination and distortion estimation. CVGIP, vol 38, pags. 299-316, (1987).
- [6]. P.K. Sinha, F.Y. Chen, R.E.N. Horne. Recognition and location of shapes in the Hough pattern space. IEE Elect. Div. Colloq. on Hough transform, 1993/106. Savoy place, London, (May 1993).
- [7]. J. Montenegro Joo. – L. Da Fontoura Costa – R. Köberle. Geometric-Transformation- Invariant Pattern Recognition with Hough Transforms and Distance-Discriminator Neural Networks. Workshop sobre Computação de Alto Desempenho para Processamento de Sinais. São Carlos, SP, Brasil, (1993).
- [8]. R. J. Schalkoff. Digital image processing and computer vision. John Wiley & Sons Inc. (1989).
- [9]. G. Gerig G. and F. Klein. Fast contour identification through efficient Hough transform and simplified interpretation strategy. IJCP-8, Paris, 498-500, (1986).
- [10]. J. Montenegro Joo. A Polar-Hough-Transform Based Algorithm for the Translation, Orientation and Size-Scale Invariant Pattern Recognition of Polygonal Objects. UMI Dissertations LD03769, 1998.
- [11]. J. Montenegro Joo. Geometric-Transformations Invariant Pattern Recognition in the Hough Space. Doctoral Degree Project. Cybernetic Vision Research Group, Instituto de Física de Sao Carlos (IFSC), Dpto. de Física e Informática, Universidade de Sao Paulo (USP), Sao Carlos, SP, Brazil. (August 1994).
- [12]. J. Montenegro Joo, L. Da Fontoura Costa, R. Koberle. Invariant Pattern Recognition in the Hough Space. Submitted to Electronics Letters, 1994.