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Automatic classification of products in the industry via invariant boundary moments

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ABSTRACT

The technique of the Invariant Boundary Moments (IBM) is applied to the automatic classification of two different randomly selected objects, independently of their size, position and orientation. It is shown that if the objects differ only in position and orientation (size is maintained), the power of the IBM is optimum; however when variations in size are included, overlapping results in the IBM show up, placing strong limitations to their use as a classifier tool, in cases like these a pre-defined margin of tolerance must be introduced.

Keywords: Artificial intelligence, invariant pattern recognition, cybernetic vision, boundary moments, automatic classification, industrial applications.

CLASIFICACIÓN AUTOMÁTICA DE PRODUCTOS EN LA INDUSTRIA VÍA MOMENTOS INVARIANTES DE BORDE

RESUMEN

La técnica de los Momentos Invariantes de Borde (MIB) es aplicada a la clasificación automática de dos diferentes objetos seleccionados al azar, independientemente de sus dimensiones, posición y orientación. Se muestra que si los objetos difieren solo en posición y orientación (sus dimensiones se mantienen), el poder de los MIB es optimo; sin embargo, cuando se incluyen variaciones en las dimensiones, los valores de los MIBs se superponen, lo cual limita su uso como una herramienta de clasificación, en casos como estos, debe introducirse un margen de tolerancia predefinido.

Palabras Clave: Inteligencia artificial, reconocimiento de patrones invariantes, visión cibernética, momentos de borde, clasificación automática, aplicaciones industriales.

INTRODUCTION

The Moment Invariants as a means to carry out pattern recognition of objects were introduced in the early sixties by M. K. Hu[1, 2], these "traditional" or "massive" invariants operate on the coordinates of all the pixels in the object to be evaluated.

After Hu, several research reports have been produced dealing with shortcut ways to compute the massive moment invariants[3-9].

In 1993 C.C. Chen[10] introduced the Improved Moment Invariants, this is a reformulation of Hu's moments and they are a set of invariants devised in such a way as to be evaluated on the object boundary (edge) pixels only.

In the research being reported here the invariant boundary moments (IBM) have been applied to different instances of two different metallic objects, a hanger and a L-shaped holder, see fig (1).

THE C.C. CHEN'S IMPROVED BOUNDARY MOMENTS.

The Chen's improved (edge, boundary) geometrical moments are given by

$$m_{pq} \quad \int_C f(x,y)\, x^p y^q dl \qquad p,q \quad 0,1,2,.... \qquad (1)$$

where the line-integral is to be evaluated along the object edge (boundary) C.

Discretizing m_{pq} results in

$$m_{pq} \quad \sum_{(x,y)\ C} f(x,y)\, x^p y^q \qquad (2)$$

The coordinates of the object Centroid (x_c, y_c) are given by

$$(x_c, y_c) \quad \frac{1}{m_{00}}(m_{10}, m_{01}) \qquad (3)$$

In this case the length of the curve C (boundary of the object) is given by $\mathbf{m_{00}}$. The boundary central moments --invariant to translation-- are given by

$$\mu_{pq} \quad \int_C f(x,y)\,(x-x_c)^p\ (y-y_c)^q\ dl \qquad (4)$$

and the integral must be evaluated along the boundary C of the object. In the discrete case $_{pq}$ above becomes

$$\mu_{pq} \quad \sum_{(x,y)\ C} f(x,y)\,(x-x_c)^p\ (y-y_c)^q \qquad (5)$$

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Since a summation may be carried-out in any order, then equation (5) has no particular restriction concerning boundary pixel sequence and the pixel coordinates (x,y) may be considered in any order, this has already been dealt with by this author[11,12,13].

The Chen's scale-normalized central moments are given by

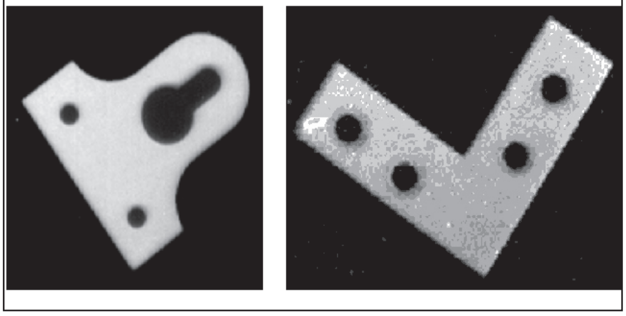
$$\eta_{pq} = \frac{\mu_{pq}}{\mu_{00}^{\,p+q+1}} \qquad p+q = 2,3,\ldots \qquad (6)$$

here μ_{00} is the length of the object boundary C. The η_{pq} are scale and translation invariant.

Chen in his improved boundary geometrical moments uses the set of seven RTS (Rotation, Translation and Size Scaling) invariant functions deduced originally by Hu[1,2] and given by:

$$\phi_1 = \eta_{20} + \eta_{02}$$
$$\phi_2 = (\eta_{20} - \eta_{02})^2 + 4\eta_{11}^2$$
$$\phi_3 = (\eta_{30} - 3\eta_{12})^2 + (3\eta_{21} - \eta_{03})^2$$
$$\phi_4 = (\eta_{30} + \eta_{12})^2 + (\eta_{21} + \eta_{03})^2$$
$$\phi_5 = (\eta_{30} - 3\eta_{12})(\eta_{30} + \eta_{12})[(\eta_{30} + \eta_{12})^2 - 3(\eta_{21} + \eta_{03})^2] + (3\eta_{21} - \eta_{03})(\eta_{21} + \eta_{03})[3(\eta_{30} + \eta_{12})^2 - (\eta_{21} + \eta_{03})^2]$$
$$\phi_6 = (\eta_{20} - \eta_{02})[(\eta_{30} + \eta_{12})^2 - (\eta_{21} + \eta_{03})^2] + 4\eta_{11}(\eta_{30} + \eta_{12})(\eta_{21} + \eta_{03})$$

Figura 1. Original photographs of the Hangers and L-shaped Holders used in the investigation.



THE INVESTIGATION

Two commercial objects produced by the hardware industry were used to carry out this investigation. The samples used were a Hanger and a L-shaped holder (Figgure 1), both are made in metal and their actual size is about 5x5 cm.

It can be seen in Chart 1, that when the number of pixels in the photographs is the same (object size is maintained) the resulting Invariant Boundary Functions are also the same (have same numerical values).

Chart 1. Hangers. Invariant Boundary functions $i\phi$ from 1 to 7

Sample	Pixels	$i\phi$ - 1	$i\phi$ - 2	$i\phi$ - 3	$i\phi$ - 4	$i\phi$ - 5	$i\phi$ - 6	$i\phi$ - 7
1	471	5.619	14.645	17.877	23.607	44.533	33.026	44.939
2	466	5.607	14.579	17.822	23.723	44.512	32.021	46.237
3	492	5.704	14.799	18.165	22.787	43.302	30.198	44.564
4	490	5.702	14.777	18.135	22.732	43.166	30.122	46.407
5	471	5.619	14.645	17.877	23.607	44.533	33.026	44.939
6	471	5.619	14.645	17.877	23.607	44.533	33.026	44.939
7	471	5.619	14.645	17.877	23.607	44.533	33.026	44.939
8	504	5.761	14.853	18.367	22.441	42.904	29.897	43.936
9	502	5.749	14.981	18.280	24.612	46.215	32.177	46.718
10	495	5.709	14.578	18.132	28.931	54.396	37.171	52.473
11	496	5.729	14.848	18.260	22.170	43.791	30.046	42.416
12	466	5.607	14.579	17.822	23.723	44.512	32.021	46.237
13	375	5.643	14.525	18.008	21.763	41.924	29.137	42.079
14	416	5.651	14.691	18.005	21.952	43.934	29.990	41.939
15	377	5.669	14.470	18.024	21.321	41.222	28.621	41.497
16	375	5.643	14.525	18.008	21.763	41.924	29.137	42.079
17	472	5.589	14.394	17.797	22.944	43.320	30.141	45.523
18	471	5.619	14.645	17.877	23.607	44.533	33.026	44.939
Min	375	5.589	14.394	17.797	21.321	41.222	28.621	41.497
Max	504	5.761	14.981	18.367	28.931	54.396	37.171	52.473

Source: Own elaboration

Figure 2. Hanger binarized (black & white) photographs. Size: 128x128 pixeles

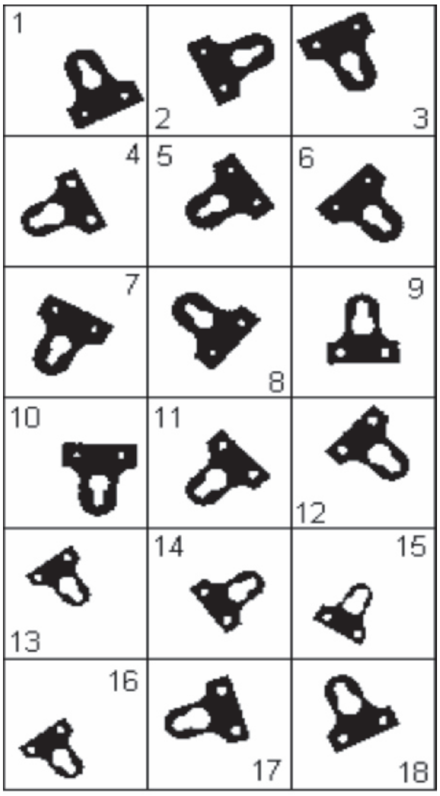


Figure 3. L-holder binarized (black & white) photographs. Size 128x128 pixeles

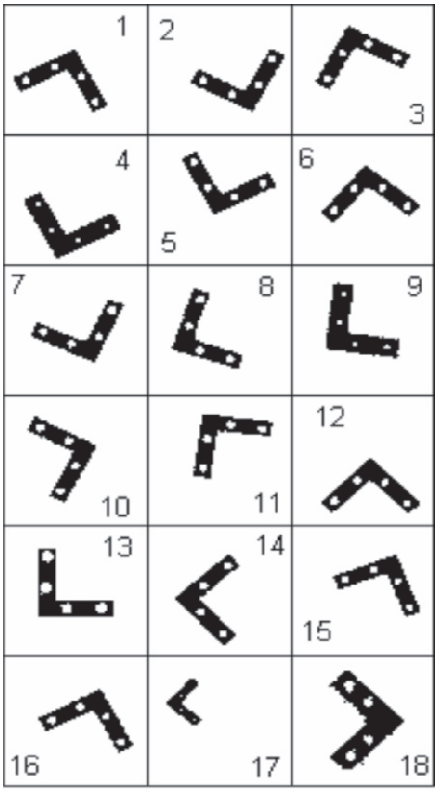


Chart 2: L-shaped holders. Invariant Boundary functions $i\phi$ from 1 to 7

Sample	Pixels	$i\phi_{-1}$	$i\phi_{-2}$	$i\phi_{-3}$	$i\phi_{-4}$	$i\phi_{-5}$	$i\phi_{-6}$	$i\phi_{-7}$
1	450	5.456	12.129	17.105	20.004	38.566	26.073	40.629
2	450	5.456	12.129	17.105	20.004	38.566	26.073	40.629
3	450	5.456	12.129	17.105	20.004	38.566	26.073	40.629
4	450	5.456	12.129	17.105	20.004	38.566	26.073	40.629
5	450	5.456	12.129	17.105	20.004	38.566	26.073	40.629
6	470	5.541	12.279	17.259	19.845	38.478	26.027	39.343
7	475	5.556	12.272	17.329	19.971	38.622	26.108	41.558
8	460	5.517	12.248	17.248	20.020	38.667	26.152	40.448
9	451	5.451	12.079	16.966	19.440	37.993	25.644	37.986
10	465	5.526	12.255	17.169	19.718	38.163	25.848	40.843
11	445	5.432	12.044	16.955	19.554	37.830	25.584	39.399
12	475	5.566	12.340	17.317	19.924	38.583	26.111	39.841
13	449	5.351	11.855	16.589	18.954	36.978	25.003	37.187
14	479	5.533	12.306	17.200	19.856	38.384	26.010	41.831
15	414	5.374	11.980	16.678	19.241	37.273	25.268	38.197
16	450	5.456	12.129	17.105	20.004	38.566	26.073	40.629
17	232	5.493	12.163	17.083	19.764	38.425	25.959	38.673
18	659	6.046	13.267	19.052	21.922	42.410	28.560	46.073
Min	232	5.351	11.855	16.589	18.954	36.978	25.003	37.187
Max	659	6.046	13.267	19.052	21.922	42.410	28.560	46.073

Source: Own elaboration

Several (128 x 128 pixel) photographs were taken to the samples, these photographs were binarized (converted to black & white) images, see Figures 2 and 3. The photographs taken show the objects in different RTS instances.

It can be seen in Chart 2, that as in Chart 1, when the number of pixels in the images is the same (scale invariance), the resulting Invariant Boundary Functions are also the same, independently of position and orientation.

In Chart 2 it can be seen that the largest object (sample 18, with 659 pixels) produced the largest values for the invariant functions, however the smallest vales were produced by sample 13, notice in Figure 3 that in this sample the sides of the object are perfectly aligned with the horizontal and with the vertical, respectively.

Comparing the minimum and maximum invariant function values, it can be seen that results for both types of samples mostly overlap, which makes it difficult to use the invariant moments as a classifier tool, except for those cases when the objects in the images have the same size.

It may be possible to use the invariant boundary moments, provided the invariant functions do not overlap, this means that given a set of objects to be automatically classified, an investigation must be made before applying these invariant moments to see whether their invariant functions overlap, if they do not, then the invariant boundary moments may be used as a classifier tool for those objects.

Otherwise there is no guarantee the invariant boundary moments will successfully discriminate the objects.

Comparing the results obtained for the Hangers with 471 pixels with those of the L-holders with 450 pixels, it results obvious that the boundary moments may be successfully used to discriminate these two kinds of objects provided their size is kept constant, see graph (1).

In Graph 1 it can be seen that provided the size of the two objects is kept constant, the invariant moments produce 5 of the 7 functions with a good margin of difference, this is, the moments have a good performance when discriminating hangers from holders, which means that this technique may actually be used to automatically classify these two objects, provided the size of both is maintained invariant.

Graph 2 shows the seven invariant functions for hangers and holders, when the investigation is made for different RTS instances. The only two functions reporting non-overlapping results are those for ϕ_2 and ϕ_6 , all the other values are overlapping, this means that in cases when the samples are different in size, orientation and position, the invariant functions have a poor performance when trying to discriminate hangers from holders.

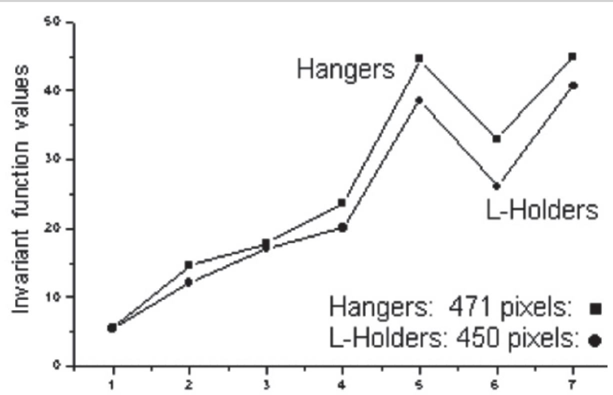
In the case shown in graph (2) the discrimination of samples strongly depends on functions ϕ_2 and, ϕ_6 for other objects this must not be necessarily true.

CONCLUSIONS

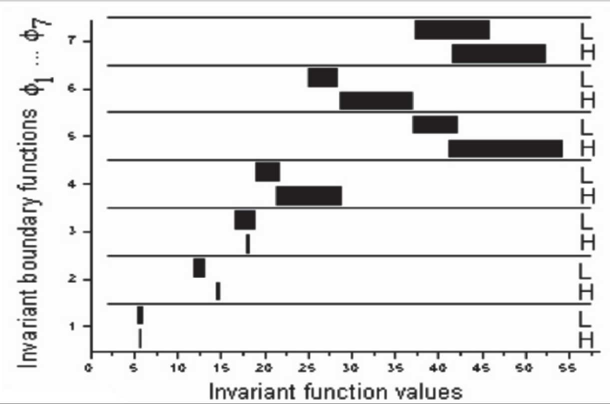
This investigation has been based on the L-shaped holder and the hanger shown in Figure 1, and it has provided important information on the behaviour of the invariant boundary moments, when applied to classification.

The recognition power of the boundary invariant moments is maximum when the size of the samples is kept constant at least for the two samples used in this research- then they may be straightforwardly used to automatically classify these objects on -for instance- a conveyor belt.

Graph 1. Invariant Boundary Functions $\phi_1 \ldots \phi_7$ for two fixet size objets.



Graph 2. Invariant Moments overlappinngs for different RTS instances of Handers and L-shaped Holders



Notwithstanding only two different objects have been used in this research, an important information have been obtained, and this dictates that when using the IBM to classify objects of different scales, an investigation must be previously carried out in order to see the performance of the IBM and thus set a margin of tolerance (fix the dimensions of a forbearance window) if necessary.

It is expected that if the invariant boundary moments were used to classify objects from a larger set, the degree of overlapping of their functions became even higher, hence weakening even more the classification power of the IBMs.

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