Hough-transform based automatic invariant recognition of metallic corner-fasteners.

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ABSTRACT

The Polar Hough Transform has been used to create a system for rotation, translation and size-scaling automatic invariant pattern recognition of polygonal objects, and it has been successfully applied to the invariant recognition of L-shaped metallic corner-fasteners. Since the performance of the developed system is autonomous it may be applied to automatic quality control and automatic classification in the industry.

Key Words: Artificial intelligence, computational vision, vybernetic vision, invariant pattern recognition, invariant shape classification, Polar Hough transform, automatic quality control.

RECONOCIMIENTO AUTOMÁTICO INVARIANTE DE SUJETADORES METÁLICOS ESQUINEROS, BASADO EN LA TRANSFORMADA DE HOUGH.

RESUMEN

La Transformada Polar de Hough ha sido usada para crear un sistema para reconocimiento invariante automático de objetos poligonales, el cual opera independientemente de la posición, orientación y tamaño de los objetos y, ha sido exitosamente aplicado al reconocimiento de sujetadores metálicos esquineros (forma de L). Como el sistema es autónomo, podría ser aplicado a la automatización del control de calidad y de la clasificación, en la industria.

Palabras Clave: Inteligencia artificial, visión computacional, visión cibernética, reconocimiento invariante, reconocimiento invariante de sujetadores, Transformada Polar de Hough, control automático de calidad.

INTRODUCTION

The Hough transform [1,4] HT, is a powerful distortion and noise tolerant technique that maps image-space points (x,y) into curves in a parameter or accumulator space. In the present work the polar, also known as Normal HT is used. It maps image-space points into a parametric accumulator space by virtue of the equation

$$\rho = x\,Cos\theta + y\,Sin\theta \qquad (1)$$

By means of this relation, any binary point (x,y) in image space X-Y is mapped into a sinusoidal in the accumulator space ρ-θ, which is discretized in cells of coordinates (ρ, θ). The main feature of the HT is that the N sinusoidals corresponding to a set of N collinear points (x_i,y_i) i=1,2,…,N meet at a point (ρ_o, θ_o) in the accumulator, the values of ρ_o and θ_o characterizing the original straight line in the image. Every sinusoidal passing by (ρ, θ) contributes with 1 to a counting stored in that location (ρ, θ). The counting stored in every cell of the accumulator corresponds to the number of points that are contained in a line characterized by (ρ, θ) in eq.(1). Due to spatial discretization, lines in image space - when Hough transformed- are usually scattered to neighbouring cells in parameter space.

Montenegro [15] has created Imagery, a full interactive Virtual Lab that allows the user to learn about the Polar Hough Transform in real time while it is executed on user defined points and lines. This Virtual Lab includes also many other topics of Digital Image Processing and Pattern Recognition.

MAIN HT PROPERTIES

The work reported here is based on the following fundamental HT properties:

- When a straight line is displaced to a parallel position in image space, only a proportional displacement along the -coordinate takes place in parameter space.
- When a straight line is rotated Ω_0 degrees in image space, its associated peak in the accumulator space is shifted Ω_0 degrees along the θ axis.
- When an object is uniformly scaled in image space, only the associated values of change proportionally in accumulator space.

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PREVIOUS RELATED WORKS

Abundant literature dealing with general behaviour of the HT can be easily found in journals, however articles like this, reporting applications of the polar HT to pattern recognition in Hough's accumulator space are rather scarce and to the knowledge of this author only two researchers have already dealt with invariant pattern recognition in Hough space; these are Krishnapuram and Casasent [3] , and Sinha et al [5], however neither of these two works considered object size-scaling. These authors use convolution in -space to achieve the rotational registration between sample objects and templates, an additional processing is then necessary to determine the translational correspondence.

THE PRESENT WORK

The system being described in this report is based on an algorithm endowed with the following advantages with respect to the two methods just mentioned lines above:

An algorithm to solve the problem of object size-scaling is developed and it is successfully applied. This algorithm is associated to a low complexity computation and to a short computing time.

When training the system there is no need to place the template object in any particular position, orientation or size, it is simply placed at random in image-space.

The Hough space features of the object to be recognized are rotated and translated only once in accumulator space, then a comparison with the stored templates is accomplished. This represents a substantial improvement respectively to the many comparisons implied by the methods used in the two works above mentioned.

In the present work the counting stored in the accumulator bins is used as an evidence of sample-template matching.

STRATEGY OF THE ALGORITHM

This author has designed and developed an algorithm which operates exclusively on accumulator space and consists in taking the Hough space features of the object to a pre-defined standard status in Hough space. In this context, “standard status” must be understood as a previously defined spatial distribution and normalized intensity of peaks in the accumulator [6,7,9,12].

The scaling problem is solved taking into account the fact that whatever the object size, the proportion among its side-lengths is translation, orientation and size-scale invariant, in this way the normalized intensity stored in the accumulator bins is always the same for any given object.

The algorithm is applied equally to training and recognition stages. After Hough transforming the image-space, a sequence of operations and transformations take place in the accumulator so that the object's Hough space features are taken to the previously defined standard status, then a characteristic vector T or S, depending whether template or sample, is extracted.

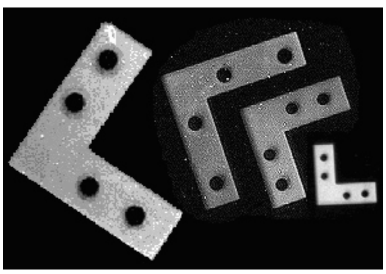
ACHIEVING INVARIANCE IN THE ACCUMULATOR (PARAMETER) SPACE

All operations leading to achieve invariance respect to position, orientation and size-scaling, are carried out in the accumulator or parameter space.

In both cases, during training and recognition the object is randomly placed on image-space in no particular position, orientation, or size. Notwithstanding, large instances of the training object should be preferred for the sake of improved accuracy.

The algorithm being reported operates on a single object at a time, thus if several ones appear simultaneously in image-space a pre-processing is

Figure 1. L-shaped metallic corner-fasteners used in woodwork to maintain firm wooden jointures with four screws. This image shows four of the twenty sample photographs used in the research.



necessary to single out individual samples. Below is included a short description of training and recognition processes, a broader description of these stages appear in [7,9,12].

THE TRAINING PROCESS

The pattern used to train the system is placed only once on image space and after Hough transforming it, a set of operations is carried out on the accumulator space so as to take the pattern to a pre-defined standard position [7,9,12,13,14], in this stage a template vector T is created and information about the votations accumulated in the characteristic peaks (ρ,θ) of the template pattern is stored, this will be used as template during the recognition process. Sometimes, depending on the special geometric features of the objects used as templates, two template vectors T_1 and T_2 may be needed, this just to make sure a good performance at recognition time.

THE RECOGNITION PROCESS

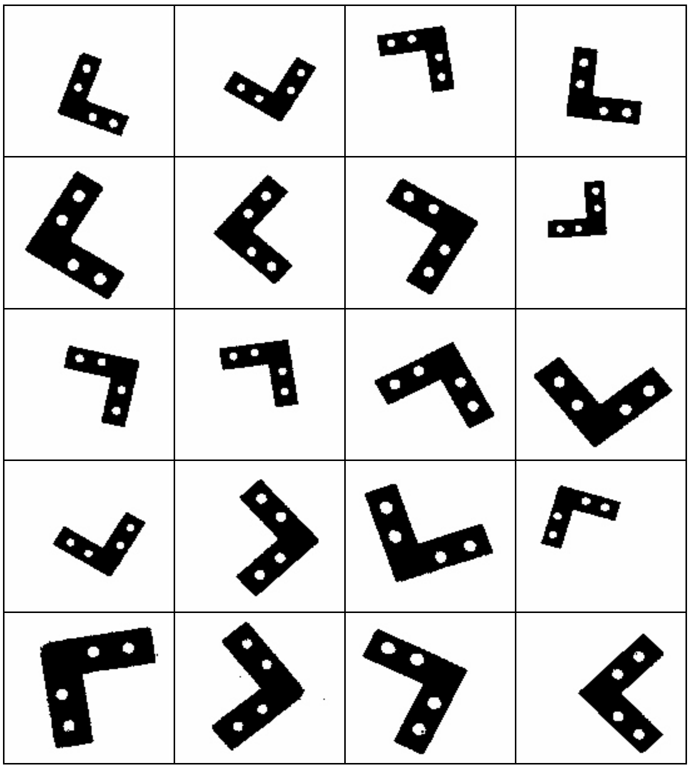
When the system is on recognition mode, the same steps carried-out at the training process must be followed for the sample to be recognized. For every incognito sample a sample-vector S is created with the corresponding values of (ρ,θ), and associated votations. In order to compare sample with template, the Euclidean distance between the two T-S pairs is computed.

THE RESEARCH

The performance evaluation of the system has been previously executed with computer-synthesized objects and with complex-shape pasteboard pieces [7,8,12]. Subsequently the method has been applied to recognize biscuits [7,8,13] and rectangular chocolates and to discriminate flawed rectangular chocolates against flawless pieces. In all cases the results show a very good performance of the algorithm [7,8,14].

This research was made with L-shaped metallic corner-fasteners used in woodwork to keep firm wooden jointures like the corner in a wooden box, see Figure 1. The twenty instances of the L-shaped metallic patterns used in the investigation are shown in Figure 2. Grey-scaled photographs were taken, scanned and converted to binary images, which were

Figure 2. L-shaped metallic corner-fasteners (used to keep firm rectangular wooden joints with four screws). Twenty Binarized photographs.



passed as input to the system. As it can be seen in the photographs, in Figure 2, input images are noise free and object edges are well defined, the metallic fasteners are six-sided and have four holes, which are used to fix them with four screws to the wooden boards making a rectangular corner. The next section justifies the use of only four Hough space features instead of six (six sides) when dealing with the L-shaped fasteners.

FOUR INSTEAD OF SIX HOUGH SPACE FEATURES

The obvious choice is to attempt to recognize the six-sided L-shaped fasteners by its corresponding six Hough space features, however when operating in this way sometimes the screw holes in the fasteners contributed to spurious accumulator peaks which this research to characterize the metallic fasteners.

RESULTS

Chart 1 displays the similitude degrees between 20 samples and the 7 pieces out of them that were randomly chosen as templates. The objects are identified as mfnn where "mf" stands for "metallic fastener" and nn ranges from 01 through 20.

It may be seen in chart 1 that, as expected, when a template is also used as a sample the resulting similitude degree is 1.00. (See the unitary diagonal in the upper portion of the chart). The same T-S similitude degree is obtained for any pair of objects one of them used as a template in a moment and as a sample in another moment. Compare results from pairs mf01 - mf02, and mf04 - mf06 and so forth.

The digits after the hyphen in chart 1 stand for the number of accumulator peaks out of searching window. It can be seen that the higher the number of peaks out of searching window, the lower the similitude degree and vice versa.

CONCLUSION

The problem of rotation, translation and size-scaling invariant pattern recognition of polygonal objects has been dealt with and an system (algorithm) based on the fundamental properties of the polar HT has been developed and successfully applied to the invariant recognition of L-shaped jointure fasteners. It is important to mention that in the designed algorithm the Hough space features of the objects are taken to a pre-defined standard status through a set of translation, rotation, and size-scaling transformations which take place just once and exclusively in accumulator space, in this way a considerable computing time is saved and the algorithm complexity is low. In this research only the four longest sides of the corner-fasteners were used to characterize the samples by means of its associated four Hough space features. Obviously if considering the six object sides the sample classification would be more accurate, but in this case some pre-processing in order to discard or refill the holes in the samples before Hough

Chart 1. Total samples: 20. The digit after the hyphen indicates the number of sample peaks out of a 2x2 searching mask.

Top horizontal row templates					Left vertical column: samples			
		mf-01	**mf-02**	**mf-03**	**mf-04**	**mf-05**	**mf-06**	**mf-07**
1	**mf-01**	1.000 - 0	0.984 - 0	0.966 - 0	0.982 - 0	0.984 - 0	0.934 - 0	0.984 - 0
2	**mf-02**	0.984 - 0	1.000 - 0	0.737 - 1	0.979 - 0	0.972 - 0	0.937 - 0	0.730 - 1
3	**mf-03**	0.966 - 0	0.737 - 1	1.000 - 0	0.982 - 0	0.725 - 1	0.967 - 0	0.972 - 0
4	**mf-04**	0.982 - 0	0.979 - 0	0.982 - 0	1.000 - 0	0.972 - 0	0.952 - 0	0.977 - 0
5	**mf-05**	0.984 - 0	0.972 - 0	0.725 - 1	0.972 - 0	1.000 - 0	0.929 - 0	0.987 - 0
6	**mf-06**	0.934 - 0	0.937 - 0	0.967 - 0	0.952 - 0	0.929 - 0	1.000 - 0	0.939 - 0
7	**mf-07**	0.984 - 0	0.730 - 1	0.972 - 0	0.977 - 0	0.987 - 0	0.939 - 0	1.000 - 0
8	**mf-08**	0.742 - 1	0.744 - 1	0.737 - 1	0.747 - 1	0.731 - 1	0.724 - 1	0.734 - 1
9	**mf-09**	0.961 - 0	0.963 - 0	0.985 - 0	0.979 - 0	0.956 - 0	0.970 - 0	0.964 - 0
10	**mf-10**	0.730 - 1	0.964 - 0	0.746 - 1	0.735 - 1	0.722 - 1	0.740 - 1	0.730 - 1
11	**mf-11**	0.742 - 1	0.732 - 1	0.735 - 1	0.737 - 1	0.740 - 1	0.722 - 1	0.747 - 1
12	**mf-12**	0.950 - 0	0.952 - 0	0.981 - 0	0.967 - 0	0.944 - 0	0.985 - 0	0.954 - 0
13	**mf-13**	0.934 - 0	0.732 - 1	0.957 - 0	0.952 - 0	0.924 - 0	0.989 - 0	0.929 - 0
14	**mf-14**	0.977 - 0	0.722 - 1	0.954 - 0	0.959 - 0	0.986 - 0	0.922 - 0	0.982 - 0
15	**mf-15**	0.982 - 0	0.970 - 0	0.730 - 1	0.989 - 0	0.977 - 0	0.947 - 0	0.981 - 0
16	**mf-16**	0.957 - 0	0.960 - 0	0.747 - 1	0.974 - 0	0.952 - 0	0.976 - 0	0.730 - 0
17	**mf-17**	0.975 - 0	0.742 - 1	0.986 - 0	0.992 - 0	0.969 - 0	0.959 - 0	0.975 - 0
18	**mf-18**	0.950 - 0	0.952 - 0	0.981 - 0	0.967 - 0	0.944 - 0	0.985 - 0	0.954 - 0
19	**mf-19**	0.954 - 0	0.957 - 0	0.742 - 1	0.972 - 0	0.950 - 0	0.980 - 0	0.954 - 0
20	**mf-20**	0.947 - 0	0.949 - 0	0.974 - 0	0.965 - 0	0.942 - 0	0.987 - 0	0.947 - 0

transformation might be necessary, in this manner the interference introduced by the holes may be eliminated at a cost of an increase in computing resources (time and processing).

SYSTEM WEAKNESSES

Even though the HT is noise and distortion tolerant per se, the system reported here is sensitive to both of them. Seeing that the developed algorithm considers the counting stored in the accumulator bins, any noise particles aligned with the sample sides in image space may introduce spurious counting in the accumulator, thus altering the results of the scaling normalization stage. Sampling variations, like those introduced by mechanical vibrations when input sample photographs are obtained may be responsible for distorted object sides, thus introducing spurious peaks in parameter space. A pre-processing based on repeated sampling to overcome these problems is proposed by Zhou and Lopresti [11], bear in mind however that any solution to solve problems like these has in general a non-negligible runtime cost.

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