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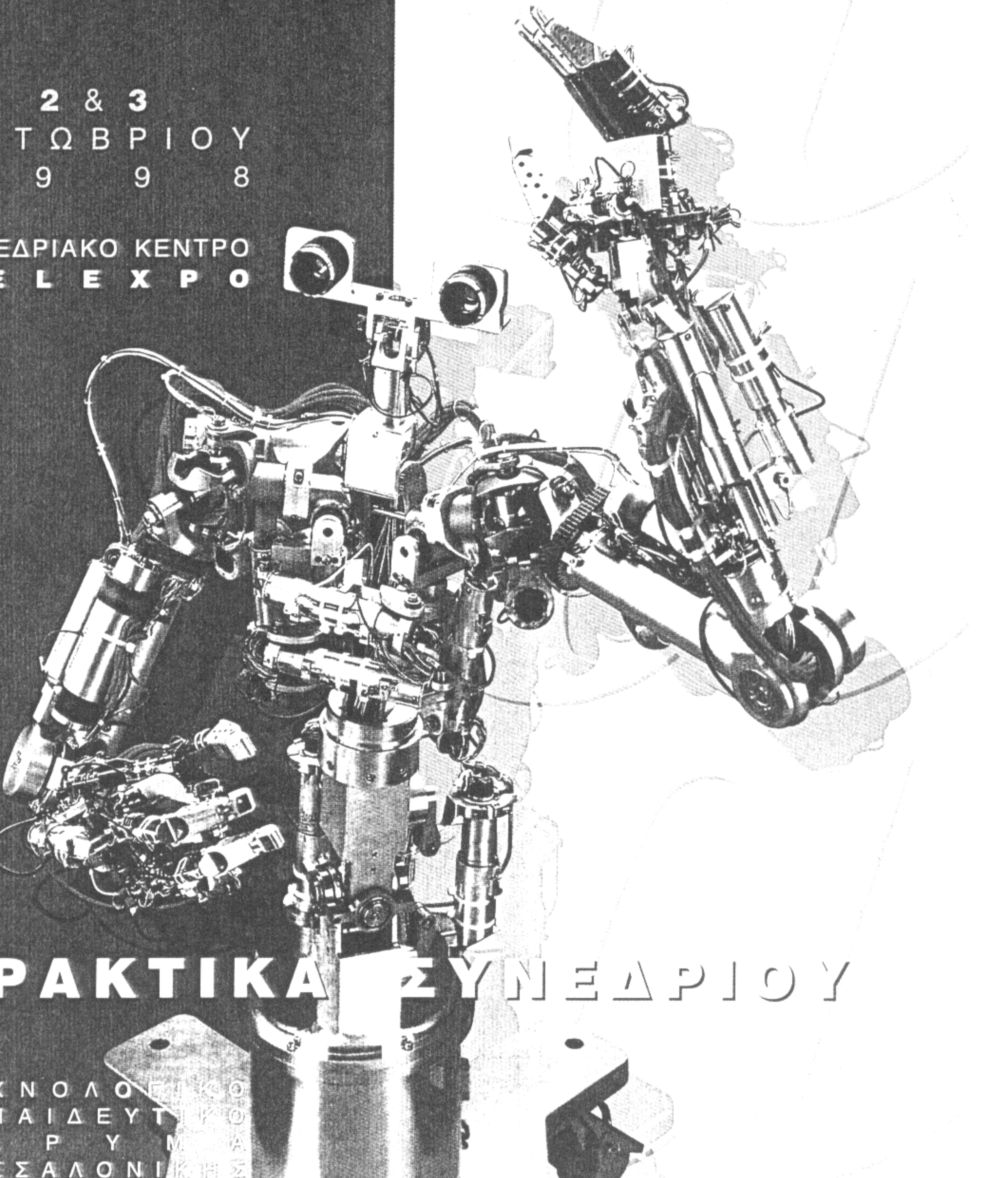

ΠΡΑΚΤΙΚΑ ΣΥΝΕΔΡΙΟΥ

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Image Block Representation and Its Applications to Manufacturing and Automation

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I. INTRODUCTION

An advantageous representation for binary images, which is called *Image Block Representation* (IBR) and constitutes an efficient tool for image processing and analysis techniques, has been recently appeared. Using the block represented binary images, real-time computation of 2-D statistical moments is achieved through analytical formulae. Using image block representation, the structural description of the object using a fast estimation of the skeleton is achieved. The image block representation method results to a set of points and all the necessary information concerning the links among them; therefore a representation of the skeleton is obtained. The structural description of the object is obtained by the classifier and is used for object learning and/or recognition. A final classifier combines the information from these two different sources (moment invariants and the structural description) and makes a decision about the classification of the input object in a certain pattern class. The Dempster-Shafer theory of evidential reasoning is used in the final classifier.

II. IMAGE BLOCK REPRESENTATION

A bilevel digital image is represented by a binary 2-D array. Due to this kind of representation, there are rectangular areas of object value 1, in each image. These rectangulars, which are called *blocks*, have their edges parallel to the image axes and contain an integer number of image pixels. At the extreme case, the minimum rectangular area of the image is one pixel.

Consider a set that contains as members all the nonoverlapping blocks of a specific binary image, in such a way that no other block can be extracted from the image (or equivalently each pixel with object level belongs to only one block). It is always feasible to represent a binary image with a set of all the nonoverlapping blocks with object level. This representation is called *Image Block Representation* (IBR).

The IBR concept leads to a simple and fast algorithm, which requires just one pass of the image and simple bookkeeping process. In this pass all object level intervals are extracted and compared with the previous extracted blocks. A block represented image is denoted as:

$$f(x, y) = \{b_i : i = 0,1,\dots,n-1\} \qquad (1)$$

where n is the number of the blocks. Each block is described by four integers, the coordinates of the upper left and down right corner in vertical and horizontal axes.

III. COMPUTATION OF MOMENTS

Since the background level is 0, only the pixels with level 1 are taken into account for the computation of the moments. Therefore, if the image $f(x,y)$ is represented by n blocks, as it is described in (1), all the image pixels with level 1 belong to the n image blocks. Moreover if the rectangular form appeared within the blocks is taken into account, then the geometrical moments are given by:

$$m_{pq} = \sum_{i=0}^{n-1} \sum_{x=x_{1,b_i}}^{x_{2,b_i}} \sum_{y=y_{1,b_i}}^{y_{2,b_i}} x^p y^q = \sum_{i=0}^{n-1} \left(x_{1b_i}^p \sum_{y=y_{1b_i}}^{y_{2b_i}} y^q + (x_{1b_i}+1)^p \sum_{y=y_{1b_i}}^{y_{2b_i}} y^q + \ldots + x_{2b_i}^p \sum_{y=y_{1b_i}}^{y_{2b_i}} y^q \right) = \sum_{i=0}^{n-1} \left(\sum_{x=x_{1b_i}}^{x_{2b_i}} x^p \right) \left(\sum_{y=y_{1b_i}}^{y_{2b_i}} y^q \right) \qquad (2)$$

where x_{1,b_i}, x_{2,b_i} and y_{1,b_i}, y_{2,b_i} are the coordinates of the block b_i with respect to the horizontal axis and to the vertical axis, respectively. Using the rectangular form appeared within the block, the computational effort, which is characterized by the complexity $O(N^2)$ for the calculation of moment, is reduced to $O(N)$ for the calculation of moments using (2). For the computation of (2), it is adequate to calculate the following summations of the powers of x and y :

$$S^p_{x_{1b_i},x_{2b_i}} = \sum_{x=x_{1b_i}}^{x_{2b_i}} x^p , \quad S^q_{y_{1b_i},y_{2b_i}} = \sum_{y=y_{1b_i}}^{y_{2b_i}} y^q , \qquad x,y,p,q \in Z \qquad (3)$$

The above summations of the powers of x and y are given by well known analytical formulae. Therefore, the summations of (3) are calculated as: $S^p_{x_{1b_i},x_{2b_i}} = S^p_{1,x_{2b_i}} - S^p_{1,x_{1b_i}-1}$ and $S^p_{y_{1b_i},y_{2b_i}} = S^p_{1,y_{2b_i}} - S^p_{1,y_{1b_i}-1}$. It has been proved, that the computational complexity of the proposed technique is of the order of $O(L^2)$, where $(L-1, L-1)$ is the order of the moments to be computed. It has been proved that other sets of moments and specifically the central, the normalized central and the moment invariants are also computed in real time on block represented binary images.

IV. STRUCTURAL PATTERN RECOGNITION

An object normalization procedure is first executed in order to preserve rotation invariant descriptions of the objects. Specifically the maximal axis of the object is found and the whole object is rotated in such a way that the maximal axis has a vertical position and that the upper half of the image object contains the most of the object's maze.

A. Thinning

In this paper a fast noniterative thinning method for block represented binary images is presented. The method has low computational complexity, extracts only critical points and to a degree appears to have immunity to the problem of locality. For the description of the thinning algorithm, the following Definitions are used :

Group is an ordered set of connected blocks, in such a way that all its intermediate blocks are connected with two other blocks, while the first and last blocks are connected with only one block.

Junction point is called a point that it is connected with two other points and it is an intermediate point of the thinned pattern.

End point is called a point that it is connected with only one other point and it is a point of termination of a thinned pattern.

Tree point is called the point that it is connected with more than two other points and it is a point where a thinned pattern is separated to three or more parts.

Critical point is called a junction or an end or a tree point.

The locality problem is addressed in the algorithm. This is achieved by the use of a suitable neighborhood at each case. Specifically, groups of connected blocks are formed. Each group is terminated when an adjacent block does not exists for its continuation, or when two or more blocks exist for the continuation of the group. Each group defines a local neighborhood and all the necessary processing takes place in this neighborhood. Using a few simple rules for the processing, the groups are checked and labeled to certain categories:

- *Vertical Elongated groups*. For each pair of connected blocks, one junction point (the central point of the common line segment of two connected blocks) is extracted.
- *Horizontal Elongated groups*. For the extraction of the junction points the algorithm starts from the left end of an horizontal elongated group and moves to the right with constant width steps. At each step a junction point is extracted at the middle of the height of the group at this vertical position.

- *Angle groups*. Three junction points are extracted from an angle group. The two junction points are extracted due to the connections with the two groups and another one for the formulation of an angle.
- *Noisy groups*. Junction points are extracted from the noisy groups, if and only if the noisy group is connected at the ends of an elongated group.

An extension of this method is the formulation of subpatterns that are used for a structural description of the object. A subpattern is defined between each pair of the end or tree points belonging to the same block or belonging to different blocks and are connected through junction points. Another advantage of the proposed method is that it allows the structural description of elongated objects, as it is presented in the next subsection.

B. Structural Pattern Recognition

A structural pattern recognition system for elongated objects that operates in two stages is presented here. In the first stage the classification of the subpatterns that constitute the whole object takes place. In the second stage the description and the classification of the whole object is achieved.

A subpattern is a sequence of points in Z^2. The task in the first stage is the classification of the subpatterns in a specified number of the classes. These classes are defined as:

1. *L*, for a straight line segment.
2. *S*, for a semicircle.
3. *C*, for a circle.

Each subpattern is classified as one or more of the three basic classes. The classification of each subpattern is based on simple geometrical features. At first, the equation and the length (L_s) of the *Hypothetical Line* (*HL*), which passes from the first P_0 and the last P_{N-1} point of the subpattern is formed. Now the following hold:

- If the deviation of the distances from the intermediate points P_i, i = 1,2,...,*N*-2 to the *HL* is small according to the length L_s of the *HL*, then the subpattern is classified as class *L*.
- If the deviation of the distances from the intermediate points P_i, i = 1,2,...,*N*-2 to the center of the hypothetical circle, which is defined with center the centroid of the *HL* and with diameter equal to the length L_s, is small according to the radius $L_s/2$, and if the first and the last points of the subpattern are different, then the subpattern is classified as class *S*.
- If the deviation of the distances from the intermediate points P_i, i = 1,2,...,*N*-2 to the center of the hypothetical circle, which is defined with center the centroid of the *HL* and with diameter equal to the length L_s, is small according to the radius $L_s/2$, and if the first and the last points of the subpattern are the same, then the subpattern is classified as class *C*.
- In every other case, where a subpattern is not classified to any of the above three classes, then the algorithm searches for a suitable point which divides the subpattern to two new subpatterns. The separation may result to subpatterns which belong to any of the desired classes (*L*,*S*,*C*).

Each subpattern is described by its type, its position on the grid and its orientation.

V. THE FINAL CLASSIFIER

The final classifier of the vision system uses the Dempster-Shafer's rule in order to combine the evidences from two different sources of information. In the proposed system the kind of information is statistical as provided by the moment invariants and structural since it is provided by the subpatterns approach.

<u>Classification based on the moment invariants.</u>

The logarithms of the moment invariants are considered as features for the recognition in order to reduce the dynamic range. In the following the similarity measures among the feature vector $\mathbf{f}_I$ of the input object and the feature vectors $\mathbf{f}_i$ i=1,2,...,*N* of the known patterns that have been stored in a database, are performed. The measures of similarity are given by:

$$d_{Ii} = d(\mathbf{f}_I, \mathbf{f}_i) = 1 - \frac{|\mathbf{f}_I - \mathbf{f}_i|}{\sqrt{\mathbf{f}_I^2 + \mathbf{f}_i^2}}, \quad i = 1,2,\ldots,N$$

In the following these distances d_{Ii} are divided by the max{ d_{Ii} }, therefore they are normalized to the range

[0,1] and a possibility distribution is obtained π_i, i=1,2,...,N. These possibility measures are reordered in such a way that the ordered set of their focal elements to be a consonant set, i.e.:

$\pi_1 \geq \pi_2 \geq \ldots \geq \pi_N \Leftrightarrow A_1 \subseteq A_2 \subseteq \ldots \subseteq A_N$

where the set A_1 contains the pattern with the maximum similarity measure, the set A_2 contains the elements of the set A_1 and the next pattern with the second largest similarity measure, e.t.a.

Classification based on the structural information

The procedure of assigning the basic probabilities should satisfy the following requirements:

- To assign the highest basic probability to a specific pattern, if the structural description of the input object is the same with the description of the pattern.
- To assign a high value basic probability to a pattern that has a quite similar description with the input object.
- To assign a low value basic probability to a pattern that has an important different description with the input object.

A procedure that satisfies the above constraints is the following:

The half of the initial maximum basic probability (i.e. 0.5) is assigned to a pattern that has exactly the same type and location of end and tree points as the input object. Each difference at the location and the type of the end and tree points decreases the amount of the initial basic probability that is assigned to the pattern by a certain penalty value.

The other half of the initial maximum basic probability assignment (i.e. 0.5) is assigned to a pattern that has exactly the same type, locations and orientations of subpatterns as the input object. Each difference at the location of the subpatterns decreases the amount of the initial basic probability assignment by a certain penalty value. Each difference at the type and the orientation of the subpatterns decreases the initial basic probability assignment by a smaller penalty value, in the case of the same subpatterns location.

The initial basic probability assignment of a pattern is the summation of the initial basic probability resulted from the end and tree points and of the initial basic probability assignment resulted from the subpatterns.

Classification of the object.

The Dempster's rule of combination is used for the calculation of the basic probability assignments and the classification of the object to a certain class. The structural information is critical and invaluable to the whole learning and recognition process, because of its ability to discriminate among similar patterns that differ in small holes or connected components. From another point of view the statistical information provided by the moments is also important for the discrimination of different patterns with similar structure.

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