A NOVEL SHAPE DESCRIPTOR BASED ON EMPTY MORPHOLOGICAL SKELETON SUBSETS.

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ABSTRACT

In this paper a novel shape descriptor based on the empty morphological skeleton subsets is proposed. This new descriptor possesses many properties required for practical shape recognition i.e. it is non-specific, robust to scale, rotation and boundary variations. One advantage of the proposed descriptor is that the empty morphological skeleton subset pattern maybe used to distinguish different objects even with identical union of skeleton subsets. Implementation of this descriptor for recognition of objects has been successfully realized using Neural Networks.

1. INTRODUCTION

A good shape descriptor is required in many applications [1]. Mathematical Morphology is an approach based on shape and hence well suited to the problem of shape recognition [2]. The Morphological Skeleton is a unique tool which can provide qualitative information about an objects size and shape [3].

Fig. 1 represents a rectangle which has undergone the morphological skeletonisation process. The shape boundary represents the original object. Grass fires have been started on all four sides and allowed to propagate towards the center homogeneously.

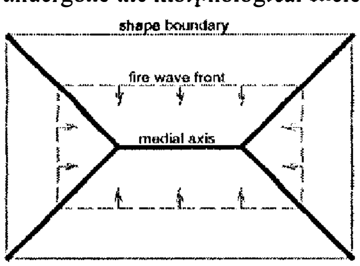


Fig. 1: Medial Axis Transform

Points where the fire wave fronts intersect, are recorded along with their arrival times and labeled as skeleton points. Using this analogy the skeleton or medial axis of the object is generated as seen by the thick line in Fig. 1. During this process each frame containing the specific intersecting points are sequentially stored, and labeled as morphological skeleton subsets.

The Morphological Skeleton Transform is represented by the following formula:

$$S_n(X) = [(X \Theta (n-1)B^S) \Theta B] - [X \Theta (n-1)B^S]_B \quad (1)$$

where $S_n(X)$ is the n^{th} skeleton subset of X, and B is the structuring element (SE) [4]. As an invertible transformation, the original object can be perfectly reconstructed from its subsets and as such all of the geometric information is also contained in these subsets and knowledge of the SE [5].

Although many recognition techniques have been developed based on the morphological skeleton, they are generally used for specific and concrete tasks [6]. The union of the skeleton subsets *SK(X)*

$$SK(X) = \bigcup_{n=0}^{N} S_n(X) \qquad (2)$$

where N represents the final skeleton subset is most commonly used for characterizing shape [4]. Features such as the number of end points, curve points as well as junction points are used as discriminating factors. Although such approaches have proved viable for matching of known objects, they are less effective for general shape description. In addition, a number of problems exist, in particularly their sensitivity to boundary variations [7].

2. EMPTY SUBSETS

Fig. 2 represents a 7x7 circle in the digital domain and its respective skeleton. Fig. 3 represents a 3x3 square and its respective skeleton. In this particular example both skeletons are the same when using a cross SE, and the union of the skeleton subsets is ineffective in

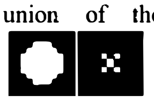


Fig. 2: 7x7 circle.

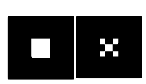


Fig. 3: 3x3 square.

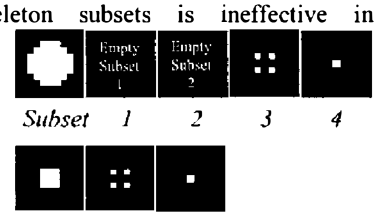


Fig. 4: Subsets for Fig. 2 & 3 resp.

distinguishing between these objects. As the technique is invertible, the difference between the two objects must be contained within the skeleton subsets. In Fig. 4, we have the same objects with their respective skeleton subsets. An obvious difference between the two is that the circle contains two empty subsets prior to the first non-empty subsets. The occurance of empty subsets gives a unique fingerprint for the shape of an object.

To emphasise the variation at the boundary, the cumulative empty subset e_k, where k is the cumulative empty subset number is defined as follows:

$$e_k = \sum_{r=N-k}^{N} G(S_r(X) = \Phi) \qquad \text{for } k = 0,1,2,\ldots,N \quad (3)$$

where $S_r(X) = \Phi$ indicates when $S_r(X)$ is an empty subset and $G(A)$ is defined as a logical function such that

$$G(A) = \begin{cases} 1, & A \text{ is True} \\ 0, & A \text{ is False} \end{cases} \quad (4)$$

Fig. 5 shows the number of skeleton subsets versus the cumulative empty subset number for a variety of objects. Each shape produces a distinctive pattern.

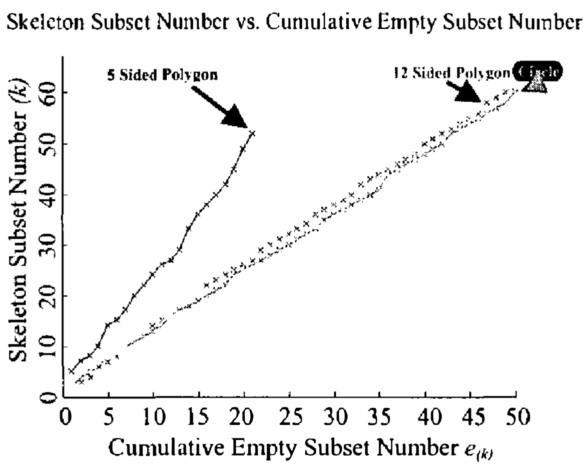


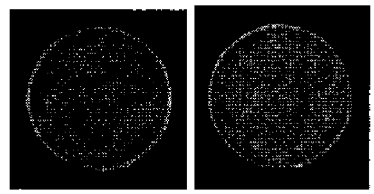
Fig. 5: Skeleton Subset number vs. Cumulative Empty Subset Number.

3. RESULTS

Several tests were performed in order to verify the properties of the empty subset patterns, i.e. robustness to scale, orientation and boundary variations.

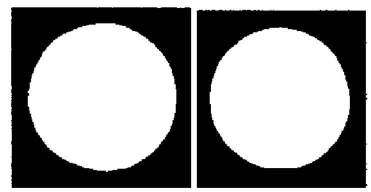
3.1 Robustness to boundary variations

Fig 6. (a) and (b) show two different one dollar coins respectively. Fig. 7 represents the binary threshold of the two coins which are used for producing the skeleton. The Pseudo-Euclidean Morphological Skeleton Transform (PEMST) is used in all experiments [8]. Fig. 8 represents the PEMST of the two coins. As a result of the boundary variations, the skeleton of the two similar size circles are considerably different.



(a) (b)

Fig. 6: One dollar coin (a) & (b)



(a) (b)

Fig. 7: Binary threshold of coin (a) & (b)

(a) (b)

Fig. 8: PEMST skeleton of coin (a) & (b)

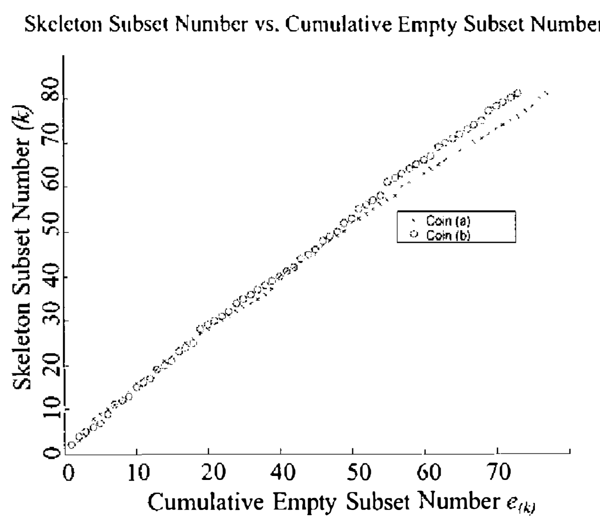


Fig. 9: Comparison of two one-dollar coins.

There is a clear correlation between the two coins based on the empty skeleton subset pattern as shown in Fig. 9.

3.2 Robustness to scale change

Fig. 10 (a) and Fig. 11(a) represent two circles of diameter 40 and 200 pixels respectively, Fig. 10 (b) and Fig 11 (b) represents their respective PEMST skeleton.

(a) (b)

Fig. 10: (a) Circle diameter 40, (b) PEMST of Circle.

(a) (b)

Fig. 11: (a) Circle diameter 200, (b) PEMST of Circle.

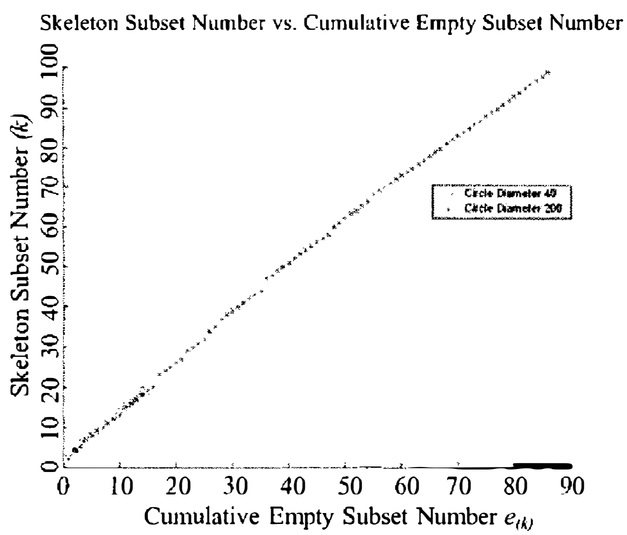


Fig. 12: Scale invariance

Using our descriptor a strong correlation in the empty subset pattern can be seen in Fig. 12, hence objects of the same shape can be recognized regardless of their scale.

3.3 Robustness to orientation

The following Fig. 13 & Fig. 14 represent two six sided polygons with a 30 degree difference in orientation. Each figure contains both the original image (a) and the PEMST skeleton (b) of that image.

(a) (b)

Fig. 13: (a) Hexagon 1, (b) PEMST.

(a) (b)

Fig. 14: (a) Hexagon 2, (b) PEMST.

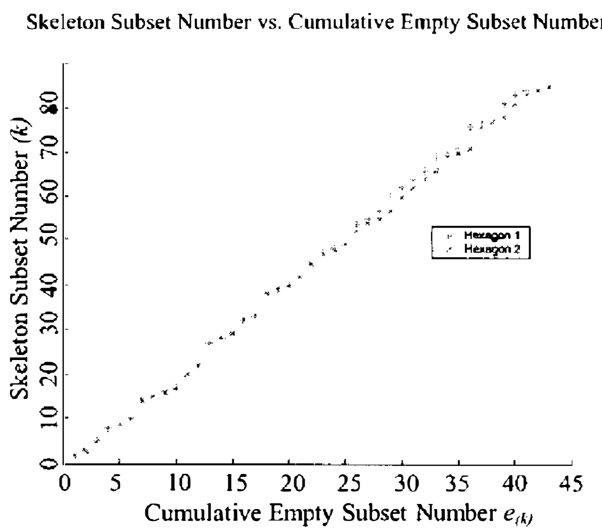


Fig. 15: Rotation invariance.

There is a strong correlation in the empty subset pattern between the two hexagons as shown in Fig. 15. As a result objects of the same shape but at different orientation can be recognized using our proposed descriptor.

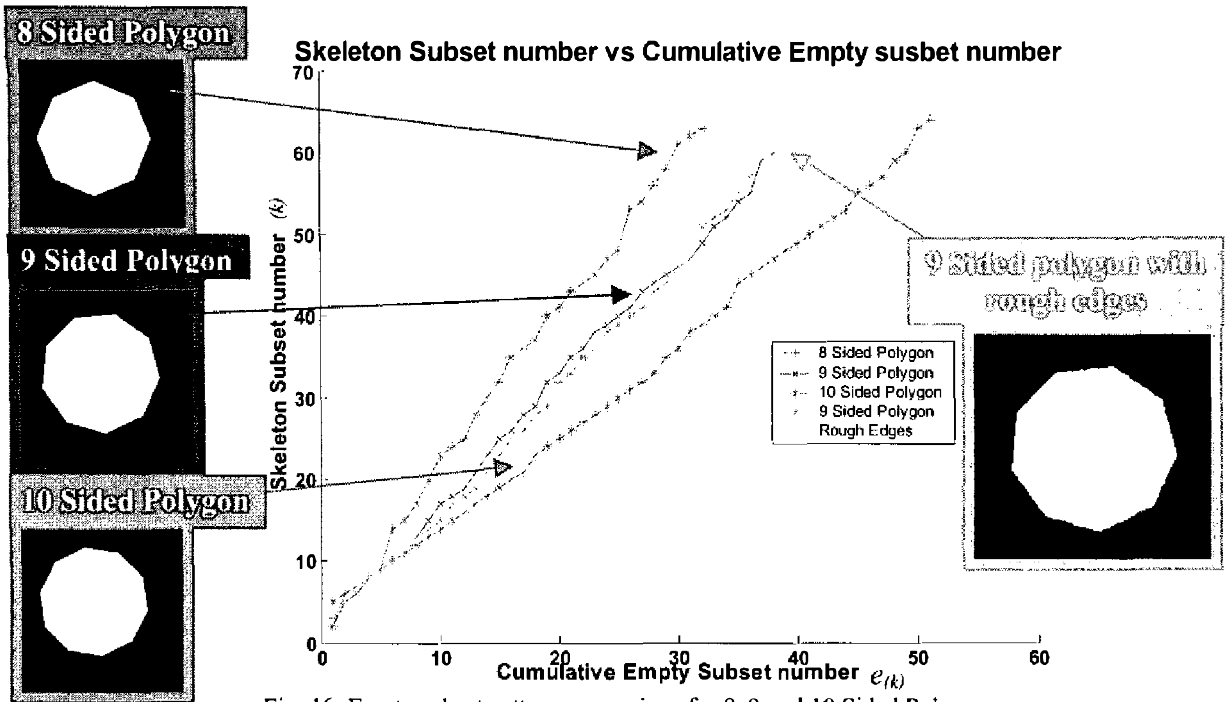


Fig. 16: Empty subset pattern comparison for 8, 9 and 10 Sided Polygons.

To illustrate the capability of our descriptor in recognizing objects of different shape, the empty skeleton subset patterns for three polygons with different number of sides namely 8, 9 and 10 were analyzed as shown in Fig. 16. Polygons with different number of sides produce a curve with different slopes. By feeding the data points in Fig. 16 into a three layer Neural Network using Back Propagation, these objects were successfully identified. As an example, a 9 sided polygon with rough edges, produced by thresholding a noisy real image was fed into the system. This 9 sided polygon was correctly identified, because its empty skeleton subset pattern best matched that of a standard 9 sided polygon used for training.

4. CONCLUSION

A new shape descriptor based on the empty morphological skeleton subset pattern has been proposed. In the digital domain, any shape can be approximated using a combination of polygons. For example a circle is a multisided polygon in the digital domain. Further research is underway to test this algorithm on more complex shapes in real images for practical pattern recognition.

A pattern recognition system has been developed using Neural Networks based on the empty subset pattern as the input to the system. The system has been able to distinguish real objects of different size and orientation successfully, when trained using only one object for each shape.

5. REFRENCES

[1] Sonka M., Hlavac V. & Boyle R., "Image Processing, Analysis and Machine Vision", Chapman & Hall, 1999.

[2] Prasad L., "Morphological Analysis of Shapes", Los Alamos National Laboratory, 1997.

[3] Maragos P. A. & Schafer W. R., "Morphological Skeleton Representation and Coding of Binary Images", IEEE Trans. on Acoustic, Speech and Signal Proc., Vol. 34 #5. 1986.

[4] J. Serra, Image Analysis and Mathematical Morphology. New York, 1982.

[5] Heijmans H.J.A.M., "Morphological Image Operators, Academic Press, Inc., New York, 1994.

[6] Ruberto, C.Di., Rodriguez, G., & Casta, L., " Recognition of shapes by morphological attributed relational graphs", 2003

[7] Kosir, J.F. Tasic, "Pattern spectrum of binary image", ICSP'98 Conference proceedings, Beijing, China, 1998

[8] Zhou, Z. & Venetsanopoulos, A.N. 1989 "Pseudo-Euclidean Morphological Skeleton Transform for Machine Vision". IEEE Int. Conf. of Acoustic, Speech and Signal Processing, p 1695-1698, Glasgow, Scotland, 1989.