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Recognition of Subjective Objects Based on One Gold Sample

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ABSTRACT

Human visual system can recognize incomplete contours and objects easily. However, these kind of recognition tasks are challenging in computer and robot vision. This paper demonstrates how combination of genetic algorithm and morphology operations can be used to generate an image processing procedure for recognition of subjective objects (e.g. incomplete objects). For this purpose, the approach receives the subjective object and the corresponding user-prepared gold sample (physical object which reflects the user's expectations). After carrying out the training or optimization phase, the optimal procedure is generated and ready to be applied on new subjective objects (the same object but with different incomplete forms, sizes, etc.). As the most important feature of this approach, it does not need any prior knowledge; the training takes place based on one gold sample. This desirable characteristic reduces the level of dependency on expert participation which is usually an obstacle for full automation in most applications. The approach architecture and the employed methodologies are explained in detail. The performance of the approach has been evaluated by several well-prepared experiments.

KEY WORDS
Subjective objects, Subjective contours, Object recognition, Object restoration, Mathematical morphology, Genetic algorithms, Optimization, Gold sample

1 Introduction

Physical (original) objects and contours usually are perceivable by sharp changing of luminance. In contrast, subjective contours/objects are nonexistent contours/objects which can be recognized by human perception although there is no luminance gradients. Some sample figures which induce subjective objects are shown in Fig.1.

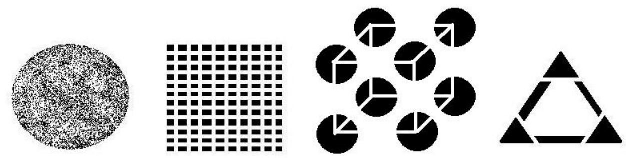

Figure 1: Some figures which induce subjective objects: Circle, square, cube, and triangle.

Recognition of subjective object/contour is a challenging topic in psychology, physiology, and also in computer vision. Most of conducted researches are in vision theory [1, 2], psychology [3, 4], and physiology [5]. This work presents a novel approach to recognize incomplete objects by utilizing one user-prepared gold sample. The proposed approach is highly invariant to object duplicating, translating, scaling, and incomplete object with different patterns.

This paper is organized as follows: Section 2 covers a short review of binary mathematical morphology because morphological operations are used to build the processing procedure. Section 3 presents the proposed architecture and methodology. Section 4 contains experimental results and finally conclusions and future work are given in sections 5 and section 6, respectively.

2 Binary Mathematical Morphology

Mathematical morphology (MM) was developed based on works by Serra and Matheron [6–8]. Morphology is a shape-based approach to image processing. The value of each pixel in the output image is based on a comparison of the corresponding pixels in the input image with the structuring element (SE). The MM techniques provide remarkable tools for image filtering [9], object extraction, and edge detection [10]. Dilation, erosion, opening, and closing are fundamental operators of mathematical morphology. Dilation expands the boundaries of the object; erosion, as a dual operation to dilation, shrinks the boundaries of the object. Objects and connections between them can be eliminated by opening with suitable structuring elements. Closing removes small holes on the foreground, which are smaller than the chosen SE. Combination of closing and opening is also known as morphological filtering [11]. In the proposed approach, these three MM operations (dilation, erosion, and opening-closing) have been utilized to build subjective object recognition procedure.

3 Proposed Approach

Fig.2 shows the main architecture of the proposed approach. It has two key units, namely, Genetic Optimizer of Mathematical Morphology Procedure, say Optimizer, and Procedure Applier, call Applier.

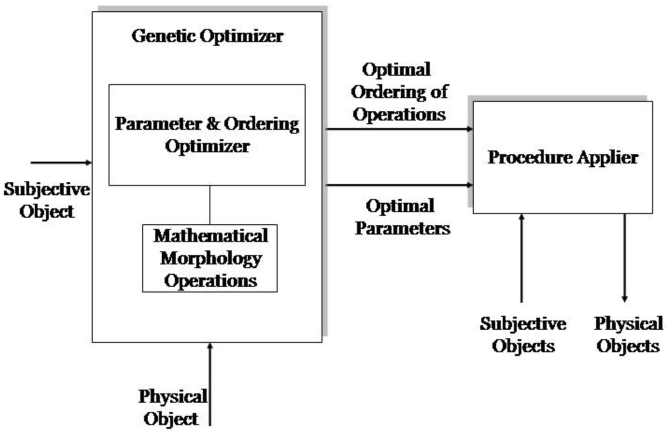

Figure 2: The main structure of the proposed approach

Genetic Optimizer- The Optimizer receives the pair of objects, namely, the subjective object, and corresponding (gold) physical object, and generates the desirable mathematical morphology procedure to achieve the object recognition effects illustrated in the gold object. The Applier applies the generated procedure on subjective objects to extract physical objects. Morphological operators are selected to build object recognition procedure because they are computationally efficient and robust shape-based image processing tools. The MM procedure uses three fundamental operators, namely, dilation, erosion, and opening-closing. Dilation and erosion can be applied more than once ($K1$ and $K2$ times); and each operator uses its own 5×5 structuring element. The six possible chains of three operators are as follows:

1. $K_3 * \{O(SE_1) - C(SE_2)\} \rightarrow K_1 * E(SE_3) \rightarrow K_2 * D(SE_4)$
2. $K_3 * \{O(SE_1) - C(SE_2)\} \rightarrow K_2 * D(SE_4) \rightarrow K_1 * E(SE_3)$
3. $K_1 * E(SE_3) \rightarrow K_3 * \{O(SE_1) - C(SE_2)\} \rightarrow K_2 * D(SE_4)$
4. $K_1 * E(SE_3) \rightarrow K_2 * D(SE_4) \rightarrow K_3 * \{O(SE_1) - C(SE_2)\}$
5. $K_2 * D(SE_4) \rightarrow K_3 * \{O(SE_1) - C(SE_2)\} \rightarrow K_1 * E(SE_3)$
6. $K_2 * D(SE_4) \rightarrow K_1 * E(SE_3) \rightarrow K_3 * \{O(SE_1) - C(SE_2)\}$

(O: opening C: closing E: erosion D: dilation. SE_1, SE_2, SE_3, and SE_4 are corresponding structuring elements. K_1, K_2, and K_3 are repetition factors for erosion, dilation, and opening-closing operators, respectively.)

The operations will be performed sequentially. For instance, $K_1 * E(SE_3)$ means that the image will be K_1 times eroded with the structuring element SE_3.

Now, the Optimizer is responsible for choosing the optimal MM procedure (one of the six combinations) and discovering the corresponding optimal 5×5 structuring elements (SE_1, SE_2, SE_3 and SE_4) and repetition factors (K_1, K_2, and K_3) for all MM operations. It should optimize the MM procedure with 104 parameters (100 variables for four 5×5 structural elements, 3 variables for K_1, K_2, and K_3, and one variable for determining the ordering of MM operators).

A template of an MM procedure has been introduced. In order to train this procedure (in fact finding the unknown parameters), an optimizer is required. Genetic algorithms (GAs) are commonly used probabilistic algorithms which mimic natural selection. They are suitable tools for function optimization, especially if we have a non-smooth objective function. The canonical GA [12, 13] has been applied here to optimize the given MM procedure (Fig.3).

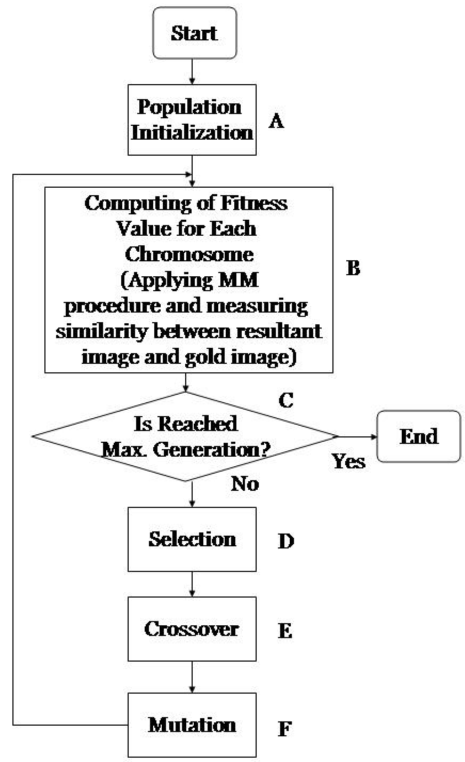

Figure 3: The flowchart of genetic optimizer of mathematical morphology procedure

The following steps describe how the GA optimizes the MM processing chain:

A. Population Initialization: Producing 20 randomly generated chromosomes as an initial population. Any chromosome is built by concatenating binary coded strings of 104 decision variables.

B. Computing Fitness Value for Each Chromosome of Population: Applying MM procedure and measuring similarity between the result and the gold images. This measure quantifies the fitness value of each corresponding chromosome.

C. Stopping Criteria: The number of generations is considered. If it exceeds a pre-specified threshold, the algorithm terminates and shows the individuals with the higher

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fitness value in the population; otherwise it goes to the next step.

D. Selection: Selecting a pre-specified number of individuals to produce offspring. The Roulette Wheel method is used to select candidates from the current population.

E. Crossover: Applying single point crossover for candidate chromosomes to produce offspring.

F. Mutation: Applying mutation as a background operator with low probability ($p = 0.01$) to generate new chromosomes resulted by randomly filliping of their bits. Go to step B.

For the proposed GA, a general and straightforward definition for a fitness function f with respect to the difference between the gold image I and resulting image $\hat{I}$ can be established as follows:

$$f = -\sum_{i=1}^{N}\sum_{j=1}^{M} \mid I_{(i,j)} - \hat{I}_{(i,j)} \mid, \tag{1}$$

where I is the $M \times N$ gold sample and $\hat{I}$ is the image generated by the MM procedure. The difference between these two images should be minimized by GA.

Procedure Applier- The Applier is responsible for executing the generated optimal object recognition procedure automatically on a group of images to recognize the target object which has been trained for.

4 Experimental Results

In order to investigate the feasibility of the proposed approach, the sample experiments are organized in four individual categories, namely, recognition of subjective circle, rectangle, triangle, and rectangle from their corners. In these experiments, the main aim is the recognition of incomplete objects, in fact, objects with missing parts.

The following GA control parameters are utilized for all conducted experiments.

Population size: 20

Mutation rate: 0.01

Maximum number of generations: 1800

Dimension of structuring elements: 5×5

Repetition factor for erosion, dilation, and opening-closing: $0 \leq K_1 \leq 20$, $0 \leq K_2 \leq 20$, and $0 \leq K_3 \leq 1$ (no more changes to the image will result from repeated opening-closing, Idempotent property)

In conducted tests, a matching index, η, between the result and the gold image is calculated as follows:

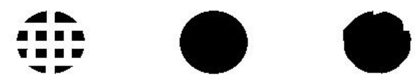
$$\eta = \frac{N - N_{UP}}{N} \times 100, \tag{2}$$

where N is the number of pixels in the input image, and N_{UP} is the number of unmatched pixels between the gold image and the resultant image. Also, the overall matching index $\bar{\eta}$ (or generalization index) is defined as follows:

$$\bar{\eta} = \frac{1}{n}\sum_{i=1}^{n} \eta_i, \tag{3}$$

where n is the number of test images.

Training for circle recognition is performed by introducing the subjective circle and the gold circle to the approach, as shown in Fig.4.



(a) (b) (c)

Figure 4: Circle recognition training set (a) subjective circle (b) gold circle (c) result circle. The resulted circle has 99.52% similarity to the gold circle.

The outputs of the training are as follows:

Optimal structuring elements:

$$SE_1 = \begin{bmatrix} 0 & 1 & 0 & 1 & 0 \\ 1 & 1 & 0 & 0 & 1 \\ 0 & 1 & 0 & 0 & 1 \\ 0 & 1 & 1 & 0 & 1 \\ 1 & 0 & 0 & 0 & 0 \end{bmatrix} \quad SE_2 = \begin{bmatrix} 1 & 1 & 0 & 1 & 0 \\ 0 & 0 & 0 & 0 & 1 \\ 0 & 1 & 1 & 0 & 0 \\ 0 & 1 & 1 & 0 & 0 \\ 0 & 1 & 0 & 0 & 0 \end{bmatrix}$$

$$SE_3 = \begin{bmatrix} 0 & 1 & 1 & 1 & 0 \\ 1 & 0 & 0 & 1 & 1 \\ 1 & 0 & 0 & 0 & 1 \\ 0 & 1 & 0 & 1 & 0 \\ 1 & 0 & 0 & 0 & 0 \end{bmatrix} \quad SE_4 = \begin{bmatrix} 0 & 1 & 0 & 1 & 0 \\ 1 & 1 & 0 & 0 & 1 \\ 0 & 1 & 1 & 0 & 0 \\ 1 & 1 & 0 & 1 & 0 \\ 1 & 0 & 0 & 0 & 0 \end{bmatrix}$$

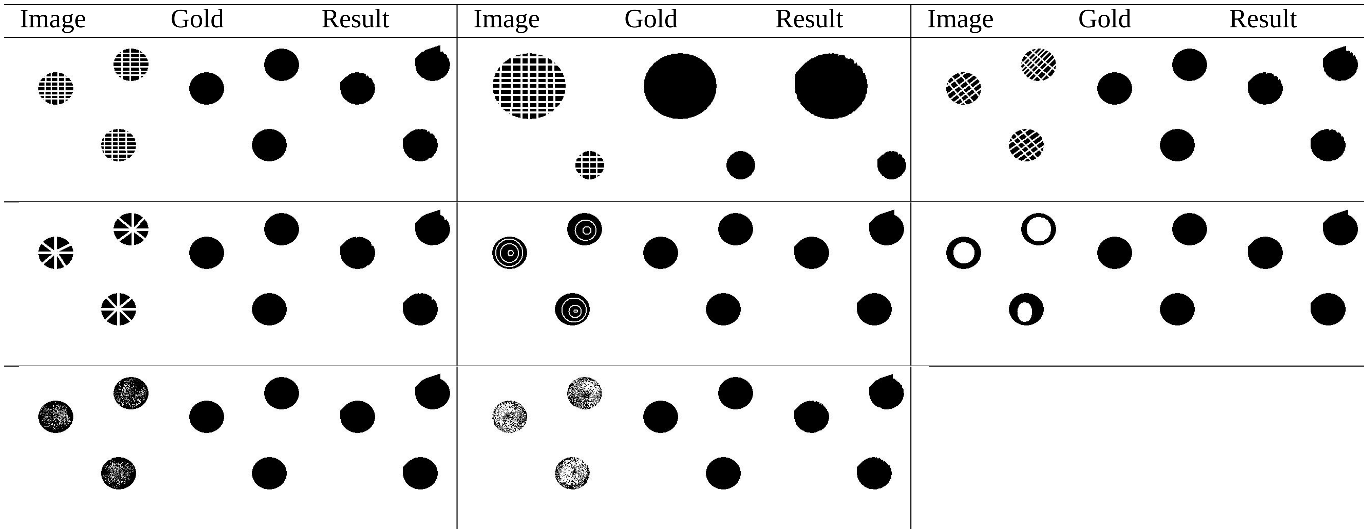
Optimal ordering (applying from left to right):

$$K_1 \times E(SE_3) \rightarrow K_2 \times D(SE_4) \rightarrow K_3 \times \{O(SE_1) - C(SE_2)\}$$

Optimal repetition factors: $K_1 = 12$, $K_2 = 12$, and $K_3 = 1$.

Now after the training phase, the optimal MM procedure can be applied to the validation set. The results of applying the generated MM circle recognition procedure to the test images are shown in Table 1. For eight test images overall matching index, $\bar{\eta}$, and standard deviation, σ, are 99.06% and $\pm 0.23\%$, respectively.

In the same manner, the training set and the results of applying generated procedure on validation set for recognition of rectangle, triangle, and recognition of rectangle from its corners are shown in Fig.5 to Fig.7 and Table 2 to Table 4, respectively. For all experiments object duplicating, translating, scaling, and objects with different patterns are included in the test set. The overall matching index, $\bar{\eta}$, and standard deviation, σ, for each experiment are given at the bottom of tables.



Overall matching index $\bar{\eta}$=99.06%
Standard deviation σ=0.2374%

Table 1: Results of applying circle recognition procedure on validation set. Object duplicating, translating, scaling, and objects with different patterns are included in the test set.

(a) (b) (c)

Figure 5: Rectangle recognition training set (a) subjective rectangle (b) gold rectangle (c) result rectangle. The resulted rectangle has 100% similarity to the gold rectangle.

(a) (b) (c)

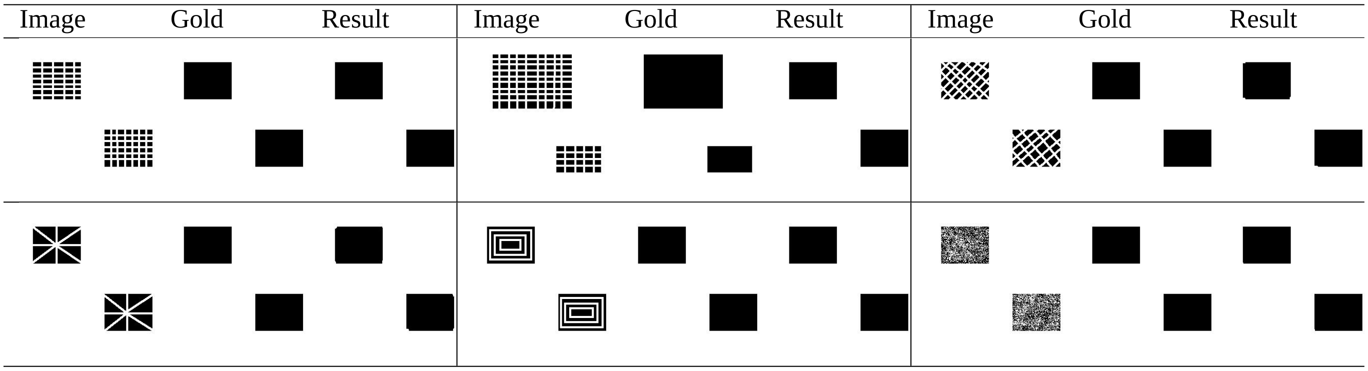
Figure 6: Triangle recognition training set (a) subjective triangle (b) gold triangle (c) result triangle. The resulted triangle has 99.89% similarity to the gold triangle.

5 Discussions and Conclusions

The proposed approach learns recognition of subjective objects from one user-prepared sample. Learning based on a small number of sample images can be very useful in the image processing field because preparing gold samples is a time and cost consuming task. For instance, in medical image processing field, preparing a large number of samples is not possible and an obstacle for research and development. In this approach, a single training phase is needed for the acquisition of the object recognition procedure. After carrying out the training phase, the optimal MM procedure is available to be applied to a large group of images. Four individual sample experiments are done. The results are promising, summarized in Table 5. The approach could successfully cope with object duplicating, translating, scaling, and objects with different patterns included in test set. The overall matching index, $\bar{\eta}$, for three cases is higher than 99%. Only for rectangle recognition from its corners, overall matching index is about 89% with standard deviation of 7.57%. In this experiment, the most affecting distortion happened when the corners were displaced; it is predictable because our training was based on shape's corners. The generated MM rectangle recognition procedure from corners could handle object translating, scaling, corner translating, adding more points, and duplicating. The outstanding characteristic of this approach is that the optimal recognition procedure can be achieved by utilizing one user-prepared gold sample without need to any prior knowledge.

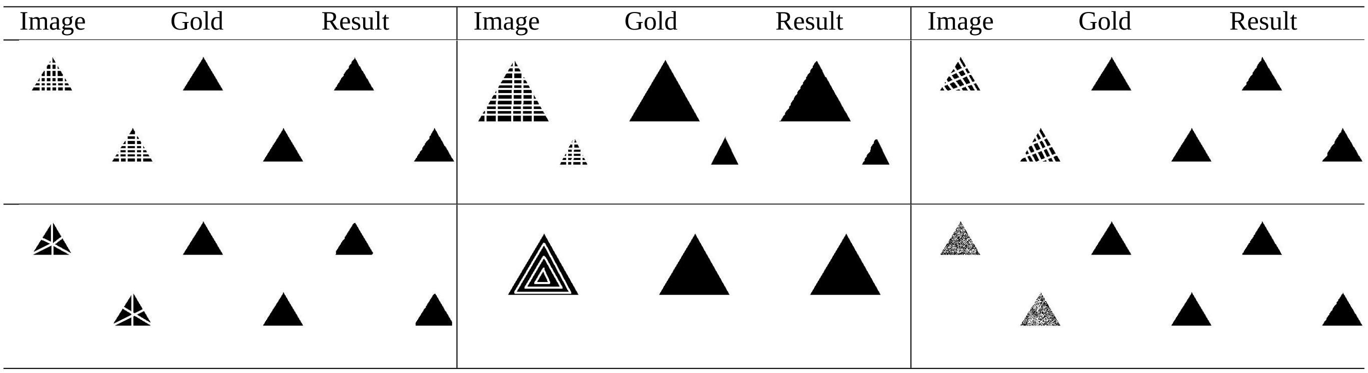
6 Future Work

The next step is to extend the current approach to grey-level images by utilizing grey-level morphology, e.g. fuzzy morphology. Recognition of real objects instead of objects with geometric shape is the another direction for the future



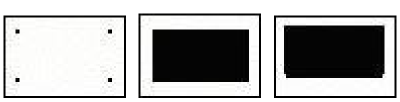
Overall matching index $\bar{\eta}$=99.90%
Standard deviation σ=0.1347%

Table 2: Results of applying rectangle recognition procedure on validation set. Object duplicating, translating, scaling, and objects with different patterns are included in the test set.



Overall matching index $\bar{\eta}$=99.73%
Standard deviation σ=0.1624%

Table 3: Results of applying triangle recognition procedure on validation set. Object duplicating, translating, scaling, and objects with different patterns are included in the test set.



(a) (b) (c)

Figure 7: Rectangle recognition (from its corners) training set (a) subjective rectangle (b) gold rectangle (c) result rectangle. The resulted rectangle has 99.78% similarity to the gold rectangle.

Object recognition task	η	n	$\bar{\eta}$	σ
Circle	99.52	8	99.06	0.23
Rectangle	100	6	99.90	0.13
Triangle	99.89	6	99.73	0.16
Rectangle from its corners	99.78	8	89.56	7.57

Table 5: Summary of numerical results for each subjective-object recognition task: Similarity, η, of the generated image after the training phase compared to the user-prepared image, number of the images used for the validation set, n, overall matching index, $\bar{\eta}$, (generalization index), and standard deviation of generalization σ.

work.

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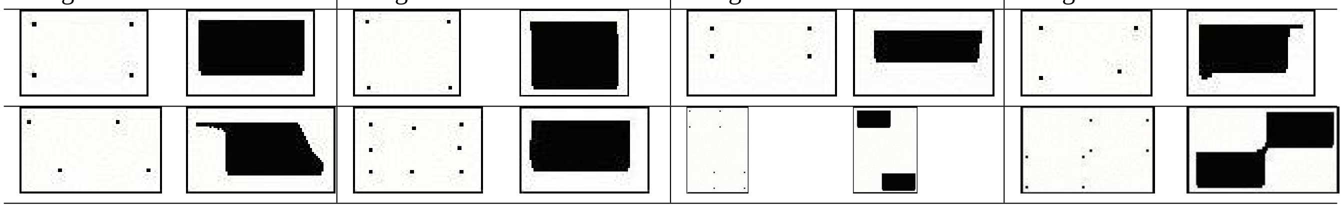
Image	Result	Image	Result	Image	Result	Image	Result



Overall matching index $\bar{\eta}$=89.56%
Standard deviation σ=7.57%

Table 4: Results of applying procedure of rectangle recognition from its corners on validation set. Object translating, scaling, corner translating, adding more points, and duplicating are included in the test set.

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