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Paper:

Automatic Acquisition of Image Filtering and Object Extraction Procedures from Ground-Truth Samples

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Knowledge- and sample-based learning approaches play a pivotal role in image processing. However, the acquisition and integration of expert knowledge (for the former) and providing a sufficiently large number of training samples (for the latter) are generally hard to perform and time-consuming tasks. Hence, learning image processing tasks from a few gold/ground-truth samples, prepared by the user, is highly desirable. This paper demonstrates how the combination of an optimizer (e.g., genetic algorithm) and image processing tools (e.g., parameterized morphology operations) can be used to generate image processing procedures for image filtering and object extraction. For this purpose, the approach receives the original and the user-prepared image (filtered image or image with extracted target object) as a gold sample which reflects the user's expectations. After carrying out the training or optimization phase, the optimal procedure is generated and ready to be applied to new images. The feasibility of our approach is investigated for two individual image processing categories, namely filtering and object extraction, by well-prepared synthetic images. The proposed architecture and the employed methodologies are explained in detail. Experimental results are provided as well.

Keywords: image filtering, object extraction, genetic algorithm, mathematical morphology, image processing chain

1. Introduction

The rapid growth of the image processing field in a wide range of applications, from medical to industrial, has resulted in the learning and automation of image processing tasks becoming a highly desirable but challenging research field. One commonly used categorization for learning systems is *supervised* and *unsupervised* learning [1, 2]. In supervised learning, for each input corresponding outputs are given by a teacher. The system uses these inputs and outputs to learn how outputs can be generated for new inputs. In contrast, there is no explicit teacher for unsupervised learning; the system commonly uses trial-and-error, probabilistic, or competitive methods to discover the expected outputs [1, 3]. Any image processing learning approach has its own strengths and drawbacks. Most existing approaches are case-based solutions and most often, especially in complex cases, need many samples from which to learn, or supporting expert knowledge to perform a variety of image processing tasks. For most applications (e.g. medical imaging), a huge amount of training data (expert-prepared images) is hard to provide. An approach with the ability to learn image processing tasks from a small number of images is highly desirable.

The main objective of this work is to design an approach that learns specific image processing tasks from a few (ideally one) original and corresponding gold images. Providing one or a few user-prepared images is a reasonable demand, which can be satisfied in all image processing environments. The proposed approach attempts to learn image filtering and object extraction from one gold sample. For example, the approach can be trained for noise filtering by providing original and filtered images. After training, it will remove noise automatically by applying the generated filtering procedure on new noisy images in the same image category. A distinguishing feature of the proposed approach is that it has a general scheme and can be applied to both image filtering and object extraction if required.

Image filtering and object extraction both are crucial tasks in the image processing field. Our approach uses morphological operators to build image processing procedures and applies a genetic algorithm to optimize those procedures. In this work we use the words learning and optimization interchangeably

This paper is organized as follows: section 2 covers the problem statement and motivation. Section 3 surveys related work. Section 4 presents the proposed architecture and methodology. Section 5 discusses the implementation of the proposed architecture. Experiments and results are given in section 6, and finally, conclusions and future work are presented in sections 7 and 8, respectively.

2. Problem Statement and Motivation

The rapid growth of image processing applications demands automated processing tasks. Most image processing operations such as enhancement, segmentation, and classification are complex and time-consuming, whereas the final result should usually satisfy the subjective perception of an expert (e.g. in medical imaging). On the other hand, in applications with real time requirements, dependance on human interaction is not practical. These issues necessitate the attempt to automate image processing systems. The ability to learn is a highly desirable feature for such automated systems since optimal algorithm configuration is usually not straightforward.

Here, we classify the various image processing learning methods according to the purpose of our work. The major works conducted in image processing learning can generally fit into one of the three main groups, namely knowledge-based, sample-based, and search- and optimization-based learning.

Knowledge-Based Learning

In knowledge-based learning approaches, knowledge can be used explicitly (declarative knowledge) or implicitly (procedural knowledge) [4]. Knowledge-based systems principally improve reasoning, flexibility, and human-like inference. Many works have been carried out by knowledge-based systems in image processing, such as image filtering [5, 6] and object recognition [7, 8]. Building and using knowledge-based systems commonly have some difficulties such as knowledge acquisition, self-learning, and knowledge reliability. All these are common challenges, but sometimes they can be solved by combining knowledge-based systems with other methods. In spite of the mentioned difficulties, knowledge-based systems are valuable methodologies and have widely been used in practice.

Sample-Based Learning

The second category is sample-based learning. In this category, the system learns from input images and corresponding outputs which are presented to it. The most common tools used for sample-based learning in image processing are Artificial Neural Networks (ANNs) [9]. The majority of works performed by ANNs are in preprocessing [10]. Most of these approaches use pixels or features as input data. General advantages of using ANNs are: example-based learning, inherent parallelism, low programming effort and cost, and domain-knowledge independency. Beside these advantages, there are some drawbacks with ANNs such as problem of choosing the best architecture, their black-box nature, and the problem of providing a sufficiently large number of training samples. After broadly exploring applications of ANNs in image processing, Peterson et al. [10] conclude that ANNs can play a supporting role in image processing but not a major one.

Search- and Optimization-Based Learning

The third category is search- and optimization-based learning. Generally speaking, learning in this category is based on applying search methods on the solution space or applying optimization techniques. There are many different methods in this category applicable to solve a wide range of science and engineering problems with complex solution spaces. In many cases, the definition of a fitness or evaluation function is needed (e.g. reinforcement learning [11] and genetic algorithms [12]) to establish a measure of solution accuracy or quality. Usually designing these functions takes considerable effort. As well, these methods support case-based definitions and assumptions such that the scope of solutions is limited. Template matching is another example in this category which has a low running speed because of using template windows and pixel-based comparisons [13–15].

In comparing the above mentioned approaches and considering that knowledge acquisition and providing training data are not always possible, our proposed approach is a type of supervised search and optimization technique with the following characteristics:

a. Supporting a general scheme for image filtering and object extraction

b. No dependency on prior domain knowledge or huge number of sample images - The proposed approach should learn image filtering and object extraction from (ideally) one gold sample without dependency on expert knowledge or a large number of user-prepared samples.

c. Training for a group of images - Training and optimization should be performed (ideally) just one time for a specific category of image processing tasks and for a group or category of images.

d. Straightforward and general definition of fitness or evaluation function - The fitness function should have a straightforward and general definition for both image filtering and object extraction tasks. In other words, the definition of a fitness function should not be task- or application-based. The most commonly used metrics to compare two images are the mean absolute error (MAE) and mean square error (MSE) [16, 17]. For the binary images, misclassification error (ME) [18], a simplified version of MAE, has been used.

e. Combining robust tools - The approach should combine robust image processing tools with an optimization tool to learn a wide range of image processing tasks.

These requirements are ideal and generally hard to achieve. In this paper we choose mathematical morphology (MM) as an image processing toolset because these operations perform a wide range of image processing tasks, such as image filtering, object extraction, and edge detection [19]. For few decades, genetic algorithms (GAs), developed by Holland [20], are widely used to solve broad range of optimization problems in science and engineering [21]. For current work, they are chosen as an optimizer because of their following useful advantages comparing to other traditional optimization methods [22, 23]:

- They optimize complex functions with continuous and/or discrete variables.

- GAs do not need derivatives information or other auxiliary knowledge.
- They are well-suited for parallel processing.
- GAs are suitable for function optimization with highly dependent variables.
- They are capable to find global solution for functions with many local optima.

All above mentioned characteristics are crucial features for our current work.

3. Related Works

Only a few works have examined the combination of GA and MM to build optimum image processing procedures. Joo et al. generated MM procedures automatically by the replacement of MM operations with predicate logic [25]. However, the work was mainly an optimal substitution and not an automatic procedure acquisition. Hasegawa et al. used some image processing subroutines (e.g. binarization, smoothing and contour tracking) to build a desired processing sequence [26]; naturally, the domain of image processing tasks and their performance directly depend on the employed subroutines. Expert knowledge is required to include appropriate subroutines. On the other hand, the use of more subroutines increases the search space complexity drastically. Yoda et al. [27] used basic and directional morphological dilation and erosion to extract different components from musical score sheets by focusing on the sequence of the operations without investigation of the importance of size and shape of the structuring elements (SEs). Although Neal et al. [28] considered the role of the structuring elements in image filtering, due to the simplicity of the generated sequence of dilation and erosion operations, their approach is just applicable to filtering. Mahmoud et al. [29] utilized a genetic algorithm to optimize grayscale soft morphology filters with customized applications in old film archives filtering. Furthermore, there are some other few works which all consider the optimization of morphological filters by applying genetic algorithms [30–34].

All mentioned works remain task-based solutions, mostly filtering, with limited applications because of template model simplicity (limited number of operations, small number of parameters to be optimized). For these reasons, the same model cannot be applied to a wide range of image processing tasks. Simplicity here means using small number of operations, no adjustable number of repetitions for operations, ignoring the size and shape of structuring elements as adjustable parameters, etc. In contrast, the proposed approach addresses the ordering of operations, the shape of structuring elements (SEs), and a repetition factor of operations simultaneously. In addition, it uses the same image processing template for a wider range of image processing tasks, namely, image filtering and object extraction.

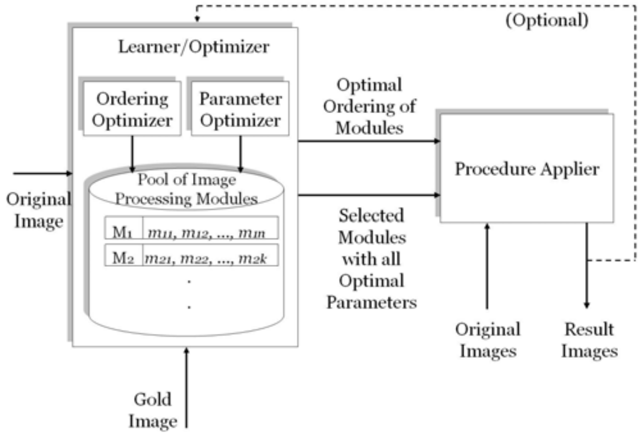


Fig. 1. The main architecture of the proposed approach.

4. Architecture and Methodology

The main structure of the proposed approach is illustrated in **Fig. 1** and has two main blocks, namely "Learner/Optimizer" and "Procedure Applier." The Learner receives the original image and the gold image -which reflects the user's expectations- and attempts to obtain an optimal image processing procedure. The Applier executes this constructed procedure for a group of images to produce images with the targeted image processing effects. The Learner has two sub-blocks, "Ordering Optimizer" and "Parameter Optimizer," and also a database of image processing modules $\{M_1, M_2, \cdots\}$ with their corresponding parameters $\{(m_{11}, m_{12}, \cdots, m_{1n}\}, \{m_{21}, m_{22}, \cdots, m_{2n}\}, \cdots\}$. The Ordering Optimizer is responsible for determining the optimal ordering of the image processing modules. The Parameter Optimizer optimizes parameters of those modules. After learning, optimal ordering of the image processing modules and their optimal parameter values are transferred to the Procedure Applier. Now the Procedure Applier is ready to automatically apply the generated optimal image processing procedure to new images and produce results with the expected image processing effects. Optionally, results of the system can be fed back into the learning process in order to improve the performance of the approach by increasing the number of gold samples (online training, a direction for our future work, see dotted connection in **Fig. 1**).

5. Implementation of Proposed Architecture

It is clear that different techniques can be used to implement the Learner, and different algorithms can serve as modules. As one possible implementation of the proposed architecture, MM operations are chosen as image processing modules (section 5.1) and a GA is employed as an image processing procedure optimizer (section 5.2).

5.1. MM Operations as Image Processing Modules

We have chosen MM operations as image processing modules because they provide practical tools for image filtering, object extraction, and edge detection [19, 35–37]. Mathematical morphology was developed based on works by Serra and Matheron [38–40] and 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 pixel in the input image with its neighbors according to corresponding structuring element [38, 41]. Dilation and erosion are fundamental operators of MM. *Dilation* expands the boundaries of the object and erosion, as a dual operation to dilation, shrinks them. *Opening* is defined as *erosion* followed by dilation and closing is defined as dilation followed by erosion. Objects and connections can be eliminated by opening. *Closing* removes small holes on the foreground, which are smaller than the chosen structuring element (SE). The combination of opening and closing is also known as non-linear morphological filtering which smoothes the object contours [41,42].

In our approach, morphological operations have been used to build the image filtering and object extraction procedures. There is a wide range of MM operators used for different purposes. But four operations – dilation, erosion, opening, and closing – are the fundamental operators in this field. In the proposed approach, the "Learner," shown in **Fig. 1**, uses opening-closing, dilation and erosion operators to build an optimal image processing procedure. Each operator has its own structuring element and also its own repetition factors (how many times they are applied), namely, K_1, K_2, and K_3 for erosion by SE_3, dilation by SE_4, and opening-closing by SE_1 and SE_2, respectively.

The six possible chains of three operators are given in **Fig. 2**. 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 "Learner" 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. The Learner 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). By this way, the proposed template covers 15 different operation arrangements in total, because each operator can be absent in our chain (it happens when the corresponding repetition factor for that operator is equal to zero ($K_i = 0$)). So, we have 15 possible chains with one, two, or three operators with all possible ordering of them.

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

Fig. 2. Six possible chains of three MM operators; applied left to right, 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.

5.2. Genetic Algorithms as Image Processing Procedure Optimizer

A template of an MM procedure has been introduced (**Fig. 2**). 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 reasonable tools for this optimization because of their advantages which have been mentioned before. The canonical GA [22, 24] has been applied here to optimize the given MM procedure.

The following steps describe how the GA optimizes the MM processing chain (parameter settings for GA are discussed in section 6):

A. Population Initialization: N randomly generated chromosomes are produced as an initial population. Each chromosome is built by concatenating the binary coded strings of 104 decision variables.

B. Applying Mathematical Morphology Procedures: The MM procedure related to each individual is applied. Parameters of that procedure are taken by decoding and mapping each chromosome to decision variables.

C. Evaluation of Fitness Value: After applying the MM procedure related to each chromosome, the difference between the gold image and the resulting image is measured by misclassification error ME. This measure quantifies the fitness value of each corresponding chromosome. A lower fitness value generally means higher similarity between the gold image and the resulting image generated by the MM procedure. The difference between these two images should be minimized by GA.

D. Stopping Criterion: The number of generations is considered as a stopping criterion. If it exceeds a pre-specified threshold, the algorithm terminates and shows the individuals with the highest fitness value in the population. Otherwise it goes to the next step.

E. Selection: A pre-specified number of individuals are selected to produce offspring. The "Roulette Wheel" method [22] has been used to select candidates from the current population. According to this method, each individual receives a slice of the wheel, the fitter ones get larger slices. For each parent selection, the wheel is spun, and owner of the selected slice is chosen as a candidate parent.

F. Crossover: A single point crossover is applied [22] for candidate chromosomes to produce offspring.

G. Mutation: Mutation with low probability is applied to generate new chromosomes through random bit flipping. The process continues from step B.

5.3. Procedure Applier

The Applier is responsible for executing the generated optimal MM procedure automatically to filter images or

Table 1. Representation of chromosome coding (K_i: repetition factor of the operation i, SE_j: structuring element of the operation j).

Bits for K_1	Bits for K_2	Bits for K_3	Bits for SE_1	Bits for SE_2	Bits for SE_3	Bits for SE_4	Bits for chain selector

extract objects. As a possible extension, the processed images can be fed back to the Learner on in order to increase the amount of training data on a continuous basis (see **Fig. 1**).

6. Experimental Verifications

In this section the feasibility of the proposed approach is investigated by sample experiments. These preliminary experiments are organized into two main categorizes:

A. Noise Filtering - in section 6.1 random, uniform, and Gaussian noise are added to synthetic test images to investigate the effect of image filtering by the proposed approach.

B. Object Extraction - extracting different objects, namely circles, rectangles, and triangles, from synthetic noisy images is investigated in section 6.2.

It will be demonstrated how the proposed approach can learn these tasks just by receiving original and gold images. The experiments are conducted with synthetic binary images. The last subsection (section 6.3) is reserved for verification of the optimality of the achieved results.

For the following experiments, the GA chromosome coding, parameters, and variables of the MM procedure are set as follows:

- Parameters coding and mapping to a chromosome: In order to form the chromosome, the individual strings containing repetition factors, structuring elements, and chain selector (a variable to select one of six possible chains) are concatenated as shown in **Table 1**.
- Population size: The size of population was set to 40 and the initial population was generated randomly by using uniform random generator.
- Selection: The Roulette Wheel method was used to select candidate parents from current population.
- Crossover: Single-point crossover function was used for generating new offsprings.
- Mutation: Uniform mutation with constant rate of 0.01 was used.
- Maximum number of generations was 1800, and used as stopping criterion.
- Dimension of structuring elements SE_1, SE_2, SE_3, and SE_4: 5×5.
- Repetition factor for erosion, dilation, and opening-closing: $0 \leq K_1 \leq 10$, $0 \leq K_2 \leq 10$, and $0 \leq K_3 \leq 1$ (no more changes to the image will result from repeated opening-closing, Idempotent property).

Above mentioned parameter setting has been achieved experimentally.

6.1. Image Filtering

Training for image filtering is performed by introducing the binary original and the binary gold images to the proposed learning approach. After training, the generated MM procedure has been applied on 19 noisy test images. In our testing set, three kinds of noise have been used, namely random, uniform, and Gaussian noise. The different noise levels and also combinations of them have been added to build the test set. Furthermore, some thin and thick lines, as well as irrelevant objects have been added to investigate the performance of the approach against the heavily noisy images with artifacts and irrelevant information. Also the effects of object translation, rotation, and scaling have been investigated.

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

$$\eta = \frac{N - 8N_{UP}}{N} \times 100\% \tag{1}$$

where N is the number of pixels in the individual image, and N_{UP} is the number of unmatched pixels between the gold image and the resultant image. The number of unmatched pixels is multiplied by 8 to magnify the dissimilarity between the resulting image and the gold sample. The level of magnification was determined empirically to match the visual expectation more realistically (a magnification factor of 1 would result in very high similarity even if many pixels are not matched). Also, the overall matching index $\bar{\eta}$ (or generalization index) is defined as follows:

$$\bar{\eta} = \frac{1}{n}\sum_{i=1}^{n} \eta_i \tag{2}$$

where n is the number of test images.

Training is performed by introducing the binary original image and the corresponding gold image to the approach. A heavily noisy synthetic image including four objects is used as the original noisy image (**Fig. 3.a**). The gold sample is the user-prepared image (**Fig. 3.b**). The aim is to remove the noise and keep the objects. The optimal structuring elements, the optimal chain of MM operations (MM procedure), and the repetition factors corresponding to each operation are generated by the training (genetic optimization) process.

The outputs of the training are as follows (no more improvement after generation 1500):

Optimal structuring elements:

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

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

(a) (b) (c)

Fig. 3. Example for noise filtering: a) sample noisy image (260 × 213), b) the corresponding gold image provided by the user, c) filtered image by generated MM procedure. The resulted image has 96.77% similarity to the gold image. This amount is remarkable since the similarity between input image and gold image is only 18.28%.

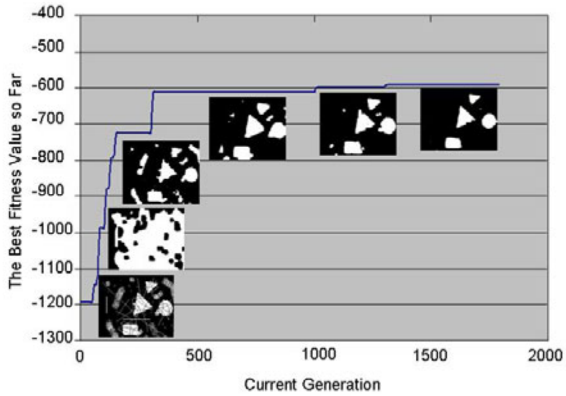


Fig. 4. The performance of the GA and improvement of the resultant image during training for image filtering.

Optimal ordering (applying from left to right):

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

Optimal repetition factors: $K_1 = 2$, $K_2 = 2$, and $K_3 = 1$.

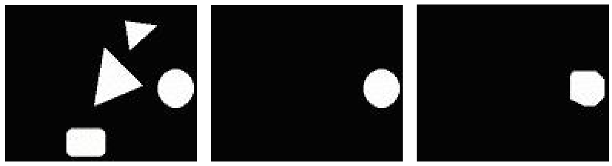
The result of applying the generated MM filtering procedure to the original image is shown in **Fig. 3.c**, with 96.77% similarity to the gold image after 1800 generations.

For the GA optimization, the graph of fitness value improvement and also the improvement of the resultant image by number of generations is shown in **Fig. 4**.

The test set contains 19 noisy images. The results of applying the generated MM filtering procedure on noisy test images are shown in **Table 2**. As demonstrated, the overall result of filtering is quite promising. In spite of using only one gold sample for learning, the optimized procedure can generalize well to new images.

6.2. Object Extraction

Object extraction or localization is one of the fundamental image processing tasks. In this section, the proposed approach is trained to learn to extract specific objects from the image. Training is performed three times to extract different shapes, namely the circle, triangle, and rectangle. After each training, the generated MM object extraction procedure is applied to the validation set. In order to evaluate the performance of approach, object overlapping, translation, scaling, duplicating, and rotation are included in the test set.



(a) (b) (c)

Fig. 5. Circle extraction: a) original image(260 × 213), b) gold image, c) the result of applying the generated MM circle extraction procedure to the original image, with η = 94.48% similarity to the gold image.

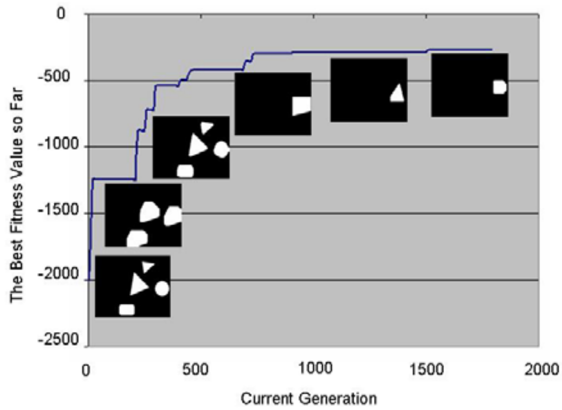


Fig. 6. The performance of the GA and improvement of the resultant image during training for object extraction.

6.2.1. Experiment 1: Circle Extraction

For circle extraction, one image including 4 different objects, namely a small triangle, big triangle, circle, and rectangle, is used as the original image (**Fig. 5.a**). The goal is to extract the circle (keeping the circle and removing all other objects) as illustrated in the gold image (**Fig. 5.b**). The optimal structuring elements, the optimal chain of MM operations (MM procedure), and the repetition factors corresponding to each operation were generated by the training process.

The results of training for this task are listed as follows:
Optimal structuring elements:

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

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

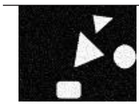
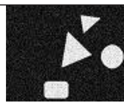
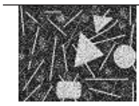
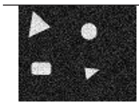
Optimal ordering (applying from left to right):

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

Optimal repetition factors: $K_1 = 9$, $K_2 = 9$ and $K_3 = 1$.

For the GA optimization, the graph of fitness value improvement and also the improvement of resultant image by number of generation are shown in **Fig. 6**.

Table 2. The results of applying the generated MM filtering procedure to noisy test images. The matching index, η, is given for each result. The overall matching index, $\bar{\eta}$ (or generalization index), is 94.81% with standard deviation of 7.80% for 19 noisy images.

Image	Result	η%	Image	Result	η%	Image	Result	η%
		98.94			98.94			98.88
		98.75			98.30			98.94
		98.46			98.48			95.99
		96.56			93.05			65.15
		92.89			89.55			96.98
		86.36			97.89			98.85
		98.49						
Overall matching index $\bar{\eta}$=94.81%								
Standard deviation σ=7.80%								

Now we have the optimal MM procedure and all the necessary parameters to apply to the test set.

The results of applying the generated MM circle extraction procedure on 6 test images are shown in **Table 3**. As seen, for all test images, the target object, circle, is extracted correctly and all non-target objects are completely removed.

6.2.2. Experiment 2: Triangle Extraction

In this experiment the goal is to extract the big triangle from the image (**Fig. 7.a**). The approach is trained and the results of training for this task are listed as follows:

Optimal structuring elements:

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

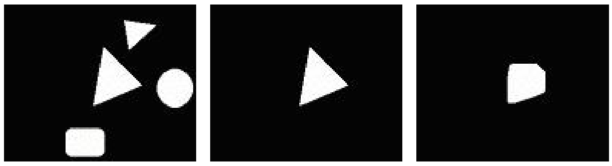
$$SE_3 = \begin{bmatrix} 0 & 1 & 1 & 0 & 0 \\ 0 & 0 & 1 & 0 & 1 \\ 0 & 0 & 1 & 1 & 0 \\ 0 & 1 & 0 & 1 & 0 \\ 1 & 0 & 0 & 0 & 0 \end{bmatrix} \quad SE_4 = \begin{bmatrix} 1 & 0 & 0 & 1 & 1 \\ 1 & 0 & 0 & 0 & 1 \\ 1 & 0 & 0 & 0 & 0 \\ 0 & 1 & 0 & 1 & 1 \\ 1 & 1 & 0 & 0 & 0 \end{bmatrix}.$$

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: $K_1 = 10$, $K_2 = 9$ and $K_3 = 1$.

The original image for training, the gold image and the result of applying the generated MM triangle extraction procedure are shown in **Fig. 7**. Now after the training phase, the optimal MM procedure is able to be applied to the validation set.



(a) (b) (c)

Fig. 7. Triangle extraction: a) original image (260×213), b) gold image, c) the result of applying the generated MM triangle extraction procedure to the original image, with $\eta =$ 85.01% similarity to the gold image.

The results of applying the generated MM triangle extraction procedure to the test images are shown in **Table 4**.

6.2.3. Experiment 3: Rectangle Extraction

The approach is trained to extract rectangles from the original image. The results of training for this task are listed as follows:

Table 3. The results of applying the generated MM circle extraction procedure to the test images. The matching index, η, is given for each result. The overall matching index, $\bar{\eta}$ (or generalization index), is 94.57% with standard deviation of 4.25% for 9 validation images. Noise, object translation, overlapping, and scaling are included in the test set.

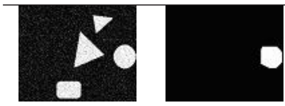
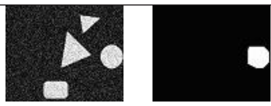
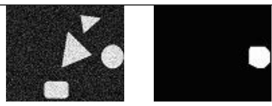
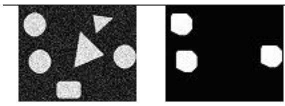
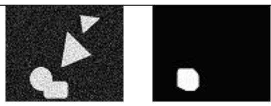
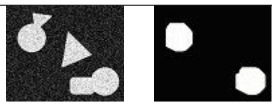
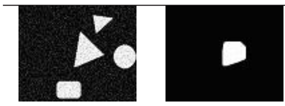
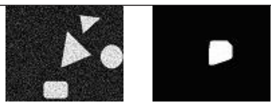
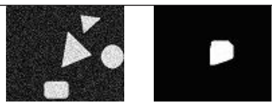
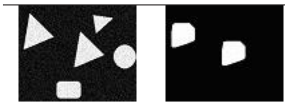
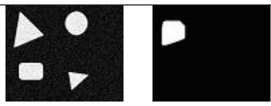
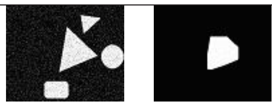
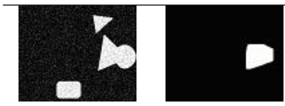
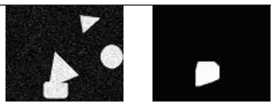
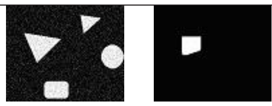
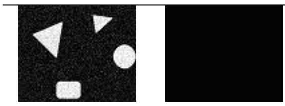
Image	Result	η%	Image	Result	η%	Image	Result	η%
		96.83			96.80			96.82
		90.48			96.80			96.98
		96.14			96.48			83.87
Overall matching index $\bar{\eta}$=94.57%								
Standard deviation σ=4.25%								

Table 4. The results of applying the generated MM triangle extraction procedure to the test images. The matching index, η, is given by each result. The overall matching index, $\bar{\eta}$, is 81.46% with standard deviation of 12.45% for 11 test images. Noise, object translation, overlapping, rotation, and scaling are included the test set.

Image	Result	η%	Image	Result	η%	Image	Result	η%
		89.45			89.33			89.41
		78.90			89.45			86.39
		88.24			89.02			84.26
		63.78			49.85			
Overall matching index $\bar{\eta}$=81.46%								
Standard deviation σ=12.45%								

Optimal structuring elements:

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

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

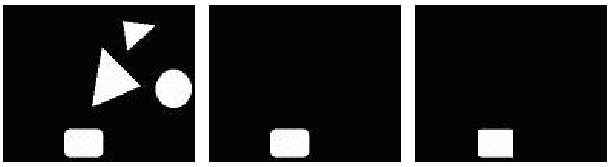
Optimal ordering (applying from left to right):

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

Optimal repetition factors: $K_1 = 8$, $K_2 = 8$ and $K_3 = 1$.

The original image for training, the gold image and the result of applying generated MM procedure are shown in **Fig. 8**. The optimal MM procedure and all necessary parameters are available to be applied to the test images.

The results of applying the generated MM rectangle extraction procedure to the test images are shown in **Table 5**. As shown, for all cases, the target object (rectangle) is extracted correctly and other objects are completely removed.



(a) (b) (c)

Fig. 8. Rectangle extraction: a) original image(260×213), b) gold image, c) the result of applying the generated MM rectangle extraction procedure to the original image with $\eta = 94.37\%$ similarity to the gold image.

Overall Analysis - The performance for object extraction in the three experiments is promising. The overall matching index, $\bar{\eta}$, for 30 images is 89.18% with standard

Table 5. The results of applying the generated MM rectangle extraction procedure to the test images. The matching index, η, is given by each result. The overall matching index, $\bar{\eta}$, is 92.61% with standard deviation of 8.12% for ten test images. Noise, object translation, overlapping, rotation, and scaling are included in the test set.

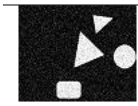
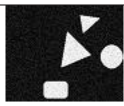
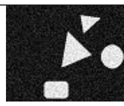
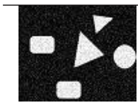
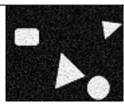
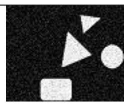
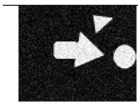
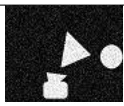
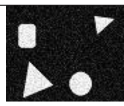
Image	Result	η%	Image	Result	η%	Image	Result	η%
		96.92			96.92			96.92
		93.84			96.92			99.55
		74.82			94.79			96.85
		78.60						
Overall matching index $\bar{\eta}$=92.61%								
Standard deviation σ=8.12%								

Table 6. Verification of generalization capability: effects of changing the parameters of the generated optimal MM filtering procedure and changing the ordering of MM operators.

Change	Result	Change	Result	Change	Result
No change		*OCDE* to *EOCD*		*OCDE* to *EDOC*	
OCDE to *DEOC*		$K_3 = 1$ to 0		$K_2 = 2$ to 3	

deviation of 10.85%. The results show that the method is highly invariant against object translation, object duplication, noising, object overlapping, and partially invariant against object scaling and object rotation (up to 90°). In 29 cases (96.66% of cases) the objects have been located correctly; just in one case, in triangle extraction, when the object was rotated 180°, it disappeared in the resulting image.

According to our expectations, when the number of target objects increases in the original image (e.g. by object duplication), the accumulation of errors (unmatched pixels) causes the decrease in matching index even when the objects are located correctly. The proposed approach shows better results for circle and rectangle extraction than triangle extraction. For triangle extraction, the similarity index is lower than the other two cases; that is because of a low similarity index in the training phase. In order to extract the large triangle, the generated MM procedure should remove the small triangle (with the same properties of the large triangle), circle, and rectangle completely and keep the large triangle. Naturally, this was not possible without accepting some distortion in the extracted large triangle.

6.3. Verification of the Results Optimality

The GA optimization was interrupted after 1800 generations for all experiments because no improvement after 1500 generation was observed. In addition, only one gold sample was used for training. Hence, the question arises: how reliable are the provided MM procedures? In this section, we want to experimentally investigate the optimality of the generated MM procedures, and how changing of the elements would affect the result. The experiments have been performed for image filtering and object extraction tasks.

For filtering and object extraction, the results of changing the elements of the generated optimal MM procedure and the changing the orderieng of MM operators are shown in **Tables 6** and **7**, respectively.

As it can be seen, these experimental investigations show that changes in parameters dramatically reduce the result accuracy. Hence, the generated MM procedures are optimal or close to optimal and their parameters are not based on randomness.

Table 7. Verification of generalization capability: effects of randomly changing the elements of the generated optimal MM object extraction procedure and changing the order of MM operators.

Change	Result	Change	Result	Change	Result
No change		Flipping $SE_1(1,1)$		$K_2 = 10$ to 20	
$K_3 = 1$ to 0		$EOCD$ to $OCED$		$EOCD$ to $OCDE$	

7. Discussion and Conclusions

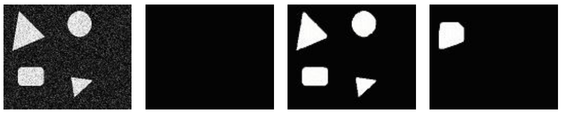
The proposed approach attempts to learn filtering and object extraction from one user-prepared sample. Learning based on a small number of sample images can be very useful in the image processing field because preparing gold samples is a time and cost consuming task, especially in biomedical environments. For instance, in the medical image processing field, preparing a huge number of samples is not possible and an obstacle for research and development. In this approach, just a single training phase is needed for the optimization of each image processing task. After carrying out the training phase, the optimal MM procedure is available to be applied on a large group of images with some specific common features.

The verification of generalization showed that the generated MM procedures are optimized and changing their parameters or changing the ordering of operations sequence worsens the result.

In section 7.1, it is experimentally investigated that chaining MM procedures can be useful to solve some type of complex image processing tasks. The summary of overall results is presented in section 7.2. Finally, the training time is discussed in section 7.3.

7.1. Chaining of the Generated MM Procedures to Handle Complex Tasks

We have already demonstrated that optimal MM procedures can be generated for specific tasks. Sometimes chaining the generated MM procedures can solve more complex problems. For example, in order to extract objects, applying the filtering procedure before applying the object extraction procedure can improve the result. An example is presented in this section which shows the usefulness of chaining MM procedures. **Fig. 9.a** presents a noisy image which includes a big triangle and three other objects. In order to extract the big triangle, the generated MM triangle extraction procedure in section 6.2 was applied, but the target object disappeared in the output image (**Fig. 9.b**). The problem is solved by applying the MM filtering procedure -generated in section 6.1- followed by the MM object extraction procedure. The results of applying filtering and then object extraction procedures are shown in **Figs. 9.c** and **d**, respectively. The matching index, η, is 87.46% and the object is clearly localized if not accurately extracted.



(a) (b) (c) (d)

Fig. 9. Solving the triangle extraction problem by chaining the MM procedures: a) original noisy image, b) result of applying the triangle extraction procedure directly on the original image leads to missing the target object, c) result of applying filtering procedure on the original image, d) result of applying the triangle extraction procedure on the filtered image; the matching index, η, is 87.46% for the final result.

7.2. Overall Results

The feasibility of the proposed approach was investigated experimentally in two different categories, namely noise filtering and object extraction. Although learning is performed just based on one sample image, the generalization index (overall matching index, $\bar{\eta}$) results for all categories is promising. The summary of the numerical results are listed in **Table 8**.

These results show that the triangle extraction has a lower overall matching index, $\bar{\eta}$, compared to others. It is predictable because the generated MM procedure should remove the small triangle (with the same properties of the big triangle), circle, and rectangle completely and keep the big triangle. This is not possible without accepting some distortion in the extracted big triangle. More training samples may reduce this effect.

The level of the supported image or object variations (namely noise addition, translating, duplicating, overlapping, scaling, and rotation) by the proposed approach is presented in **Table 9**. According to the nature of MM operations, the approach is completely invariant for object translating and duplicating. It also is highly invariant for noising, but limitedly invariant for object rotation and scaling (specially for shrinking the object). For the object overlapping, the approach is moderately invariant.

As a distinguishable feature, the proposed approach uses a general scheme applicable to both image filtering and object extraction; so it can handle a wider range of image processing tasks by the same procedure.

Table 8. Summary of numerical results for each image processing 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.

Task	η	n	$\bar{\eta}$	σ
Noise Filtering	96.77	19	94.81	7.80
Object Extraction	94.48	Circle (9)	94.57	4.25
	85.01	Triangle (11)	81.46	12.45
	94.37	Rectangle (10)	92.61	8.12

Table 9. Level of the supported image or object variations by the proposed approach (completely, highly, moderately, and limitedly supported): adding noise, translating, duplicating, overlapping, scaling, rotating.

Task	Noise Adding	Translating	Duplicating	Overlapping	Scaling	Rotating
Noise Filtering	high	complete	complete	moderate	limited	limited
Object Extraction	high	complete	complete	moderate	limited	limited

7.3. Training Time

Although, the training is a one-time task for each case; but it takes several hours and can be increased sharply if more samples are employed. There are three main reasons for this long computational time: 1) morphological operations are pixel-based tasks and so naturally expensive, 2) Genetical Algorithms (like other population-based algorithms) are computationally expensive, 3) a large-scale problem with more than 100 variables has been considered to solve; the higher dimensionality is equivalent with higher complexity. Many studies confirm that Differential Evolution (DE), an effective robust evolutionary algorithm, performs better than the genetic algorithms. Recently, the Opposition-Based Differential Evolution (ODE) [43] has been proposed by the authors and tested successfully for image thresholding [44] and solving large-scale problems [45]. Replacing GA by ODE in order to reduce the training time will be investigated.

8. Future Work

For application in medical image modalities, the next step is to extend the current approach to grey-level images by utilizing grey-level morphology or fuzzy morphology. Covering a wider domain of image processing tasks by including other morphological operations, and also improving performance of the approach by additional online training or increasing the number of sample images are other directions for future work.

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