Proceedings of the 5th WSEAS Int. Conf. on SIGNAL, SPEECH and IMAGE PROCESSING, Corfu, Greece, August 17-19, 2005 (pp248-253)

Robust Object Segmentation Using Genetic Optimization of Morphological Processing Chains

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ABSTRACT

A semi-automated object segmentation approach has been introduced in this paper. Object segmentation is a crucial task in image processing. The proposed approach learns segmentation from a small number of gold samples. The segmentation is performed in two main sequential steps, namely, target object localization, by applying optimal mathematical morphology procedure, and segmentation, by conducting some basic image processing operations. The outstanding feature of this approach is, unlike other existent approaches, that it does not need a prior knowledge or a large number of samples to learn from. The performance of the approach has been examined by a comprehensive well-designed validation set. For all test images, the target object was segmented accurately and the conducted experiments clearly showed that the proposed segmentation approach is highly invariant to noise, rotation, translation, overlapping, and scaling. The architecture of the approach and employed methodologies are explained in detail. Results are provided.

KEY WORDS
Object Segmentation, Object Extraction, Object Localization, Mathematical Morphology, Genetic Algorithms, Optimization, Learning, Gold Sample

1 Introduction

The rapid growth of the image processing field in a wide range of applications, from medical to industrial applications, has resulted in automation of image processing tasks becoming a highly desirable but challenging research field. One commonly used categorization for learning methods is *supervised* and *unsupervised* learning [1, 2]. In supervised learning, for each input corresponding outputs are provided by a teacher. The learning method 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; these methods commonly use trial-and-error, probabilistic, and competitive methods to discover the expected outputs [1, 3]. According to this characterization, the proposed approach uses a supervised learning method because the user-prepared gold samples are utilized to learn from. Any image processing learning approach has its own strengths and drawbacks. Knowledge- and sample-based learning approaches play a pivotal role in image processing [4–6]. 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 samples is highly desirable. This paper demonstrates how combination of an optimizer (e.g. genetic algorithm) and image processing tools (e.g morphology operations) can be used to generate an image processing procedure for object segmentation. For this purpose, the approach receives the original images and the user-prepared images as gold samples. After carrying out the training or optimization phase, the optimal procedure is generated and ready to be applied on new images. As the most important feature of this approach, it does not need any prior knowledge, and the training takes place based on a small number of gold samples. This desirable characteristic reduces the level of dependency on expert participation which is usually an obstacle for automation in most applications. Object segmentation is one of the crucial tasks in image processing field. The main objective of this work is introducing an approach which learns object segmentation from a few gold images. Providing a few user-prepared images is a reasonable demand, which can be satisfied in all image processing environments.

This paper is organized as follows: Section 2 describes proposed approach in details. Section 3 presents the experimental results. Finally, conclusions and future work are given in section 4 and section 5, respectively.

2 Proposed Approach

The proposed approach has two main sequential subtasks to complete segmentation, namely, object localization and object segmentation. The output of the localization phase is a portion of the target object which is used to segment that object. Fig.1 shows the main structure of the proposed approach. In this figure, the bold section of the structure shows object localization components which has two blocks, namely, Optimizer and Applier. Other blocks are the segmentation components. Both phases are described in following subsections.

2.1 Object Localization

The object localization has been performed by a chain of mathematical morphology operations. This chain has been optimized by applying canonical genetic algorithm according to presented gold (user-prepared) samples.

Genetic Optimizer - The Optimizer receives input images and corresponding gold images, and generates the desirable mathematical morphology procedure to achieve the object localization shown in the gold images. The Applier applies the generated procedure on new input images to localize the target object(s). Mathematical Morphology (MM) are selected to build object localization procedure because they are computationally efficient and robust shape-based image processing tools [7, 8]. The MM procedure uses three fundamental operators, namely, dilation, erosion, and opening-closing. *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 with a suitable structuring element. *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 [8–10]. For our MM processing chain, 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. $K_3 * \{O(SE_1) - C(SE_2)\} \to K_1 * E(SE_3) \to K_2 * D(SE_4)$
2. $K_3 * \{O(SE_1) - C(SE_2)\} \to K_2 * D(SE_4) \to K_1 * E(SE_3)$
3. $K_1 * E(SE_3) \to K_3 * \{O(SE_1) - C(SE_2)\} \to K_2 * D(SE_4)$
4. $K_1 * E(SE_3) \to K_2 * D(SE_4) \to K_3 * \{O(SE_1) - C(SE_2)\}$
5. $K_2 * D(SE_4) \to K_3 * \{O(SE_1) - C(SE_2)\} \to K_1 * E(SE_3)$
6. $K_2 * D(SE_4) \to K_1 * E(SE_3) \to K_3 * \{O(SE_1) - C(SE_2)\}$

(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). By this way, a template of an MM procedure has been introduced. In order to optimize this procedure (in fact finding the unknown optimal 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 the objective function is not smooth. The canonical GA [11, 12] has been applied here to optimize the given MM procedure.

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

A. Population Initialization: Producing 40 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 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 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:

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

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 for all given gold samples, at the same time, by GA.

Applier - The Applier is responsible for executing the generated optimal object localization procedure on group of new images to localize target objects.

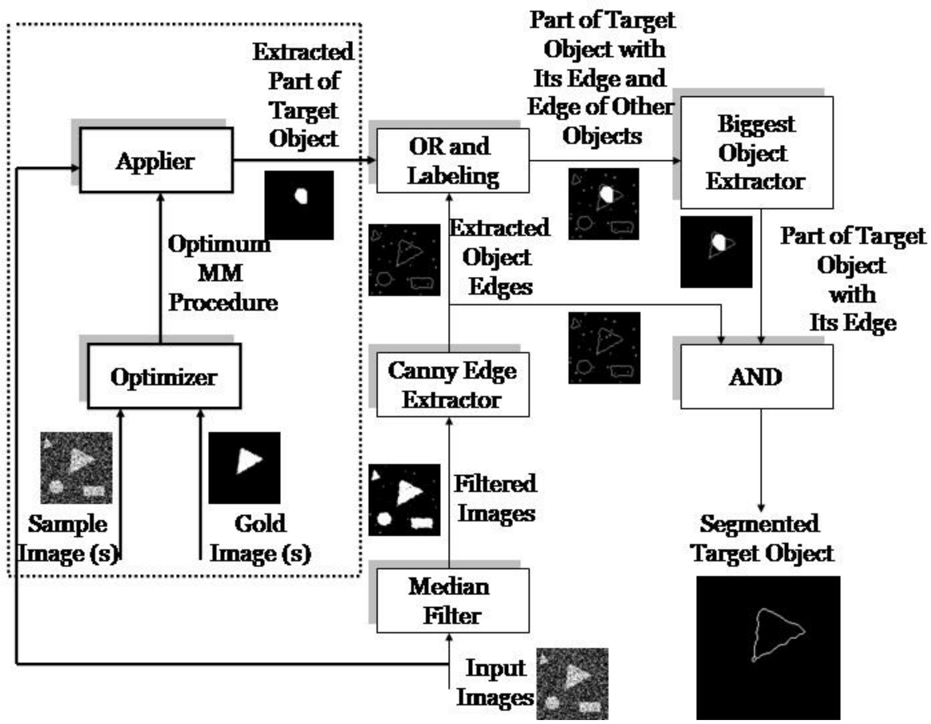


Figure 1: Main structure of the proposed approach

2.2 Object Segmentation

After object localization, we have a large portion of the target object and we should try to segment it accurately. The segmentation process is conducted by some simple sequential steps, shown in Fig.1, as follows:

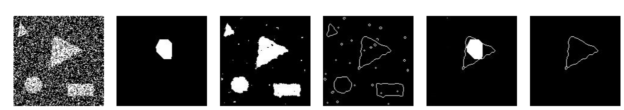
Noise removing by Median filter- The input image (i.e. Fig.2.a) is filtered in this step by median filter [13] , with 5×5 window, to remove the noise and to make it ready for the next step, edge detector. An example of filtering result is shown in Fig.2.c.

Edge detection by Canny method- In this step Canny edge detection method [14] is applied to extract edges of all objects (Fig.2.d).

Extracting a portion of the target object and its edges- Applying OR operation [8] on two images, extracted part of target object (Fig.2.b) and the output of Canny edge extractor (Fig.2.d), delivers a portion of target object with its edges and edges of other objects; finding the biggest object of this image delivers the part of the target object with its edges (Fig.2.e).

Segmentation of the target object- The final step is applying AND operation [8] on two images, result of Canny edge detector (Fig.2.d) and result of previous step (Fig.2.e), which delivers the segmented target object (Fig.2.f).

The output image for each step is shown in Fig.2.



(a) (b) (c) (d) (e) (f)

Figure 2: An example for the output image for each step of segmentation process.

3 Experimental Results

In order to investigate the feasibility of the proposed approach, experiments have been conducted in this section. The aim is segmentation of a triangle-shaped object from a synthetic image. This image includes other geometrical shapes such as circle, rectangle, and small triangle. This makes an accurate segmentation hard to achieve.

The following GA control parameters are set for this experiment:

Population size: 40; mutation rate: 0.01; maximum number of generations: 1500; 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)

Training for triangle localization has been performed by introducing the input images and also corresponding gold images to the genetic optimizer, as shown in Fig.3. To achieve a fully invariant object rotation segmentation, four input images are introduced to the optimizer; the target object, bigger triangle, is rotated four times (each time 90 degrees) and salt and pepper noise (with density, $d = 0.3$) is added to the input images. The corresponding gold images are fed to the optimizer as well. By this way, the generated optimal object localization procedure should be able to localize rotated object in a noisy environment.

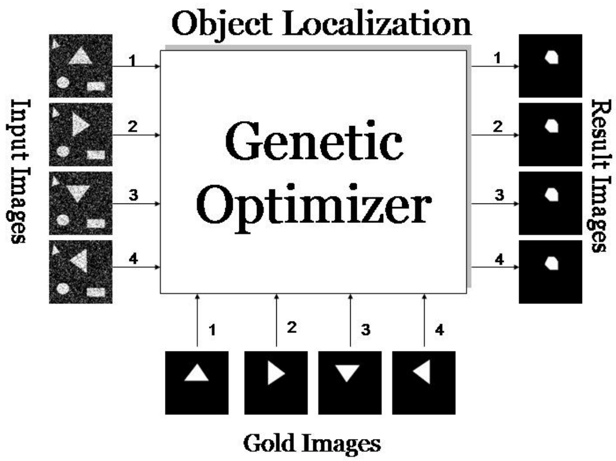


Figure 3: Training set of object localization. Input images (triangle is rotated 90 degrees each time and Salt and pepper noise (d=0.3) has been added to input images), gold images, and result images are shown. In all 4 cases the target object, triangle, is localized correctly and a large portion of the object is extracted (83.18%, 84.14%, 85.42%, and 89.12%, respectively).

The outputs of the genetic optimization are as follows:
Optimal structuring elements:

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

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

Optimal ordering (applying from left to right):

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

Optimal repetition factors: $K_1 = 5$, $K_2 = 6$, and $K_3 = 1$.

Results of optimization are shown in Fig.3. As seen, in all four cases the target object, triangle, has been localized correctly and a large portion of the object has been extracted (83.18%, 84.14%, 85.42%, and 89.12%, respectively).

Now, the optimal MM procedure is ready to be applied to new images. Then, we can follow the rest of approach for segmentation of the object. A well-prepared validation set is utilized to show the robustness of the proposed approach.

Test/Validation set - Following, a comprehensive validation set, with 80 images, has been prepared to investigate the feasibility and the robustness of the proposed approach:

Object rotation (12 times each time 30 degrees), no noise: 12 images
Object rotation (12 times each time 30 degrees), noise (salt & pepper (d=0.1)): 12
Object rotation (12 times each time 30 degrees), noise (salt & pepper (d=0.2)): 12
Object rotation (12 times each time 30 degrees), noise (salt & pepper (d=0.3)): 12
Object rotation (12 times each time 30 degrees), noise (salt & pepper (d=0.4)): 12
Object rotation (12 times each time 30 degrees), noise (salt & pepper (d=0.5)): 12
Object translating, scaling, duplicating, overlapping, image noising, and also their combinations: 8 images (the d is the density of the added noise.)

Result analysis - For above mentioned 80 test images, in 73 cases (91.25% of cases) the object was localized correctly by applying generated optimal MM object localization procedure. To overcome these 7 cases, the median filter, with 5×5 window, has been applied before feeding the image to the procedure applier. By this way, all failed cases were handled correctly. After object localization, the object segmentation steps were applied and for all 80 cases, the object was segmented accurately. Some sample results are presented in Table 1; as shown, the approach is invariant to object translating, scaling, rotating, overlapping, image noising and even combination of them. The approach is able to achieve a robust object segmentation just by using four gold (user-prepared) samples to learn from.

4 Discussions and Conclusions

The main part of the proposed approach is the object localization. Combining the mathematical morphology operations, as image processing tools, and the canonical genetic algorithm, as an optimizer, generates an optimal morphological processing chain with object localization capability. After object localization, the target object is segmented accurately by applying some basic image processing operations. For conducted experiment, the approach used four gold images to generate optimal procedure. The target object is rotated 90 degrees in each gold image to achieve a fully rotation invariant object localization procedure. A well-designed test/validation set (with 80 images) has been used to investigate the feasibility and performance of the approach. For all test images (100% of cases), the target object is segmented correctly. The conducted experiments clearly show that the proposed segmentation approach is invariant to noising, rotation, translation, overlapping, and scaling. The proposed object segmentation approach uses just a small number of gold (user-prepared) images to learn from, without dependency on any other prior knowledge. Learning object segmentation, as a crucial task in image processing, from a few gold samples is an outstanding characteristic because preparing gold samples and also gather-

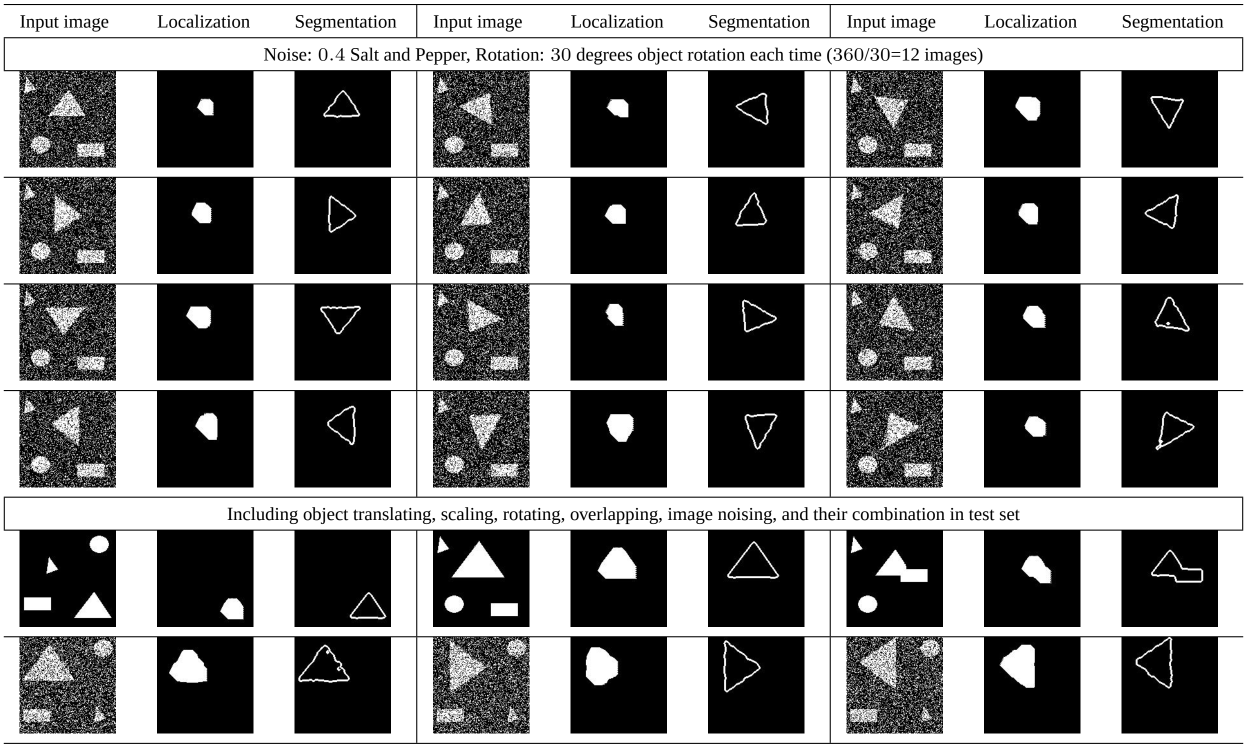


Table 1: Some results of applying triangle segmentation procedure to validation set. The result of object localization and segmentation are shown for each input test image.

ing and integration of the knowledge are cost and time consuming tasks in image processing environments.

5 Future Work

Extending the current approach to grey-level images in order to segment various tissues in medical images is the direction of our future work.

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