# A new approach to image segmentation using genetic algorithm with mathematical morphology

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***Abstract***: This paper presents a new approach to image segmentation using genetic algorithm (GA) in conjunction with morphological operations. The proposed method consists to classify each pixel of the image in pixels belonging either to the object or to the background. It starts by a configuration of individuals randomly generated, representing possible segmentation of the image. The solutions are evaluated through an appropriate fitness function which measures the similarity of the individuals with the desired solution and the fittest ones are selected to reproduce in the next generation. Then, the population progresses to a stable representation where all the individual converges to an optimal solution which is the segmented image. We show the use of the morphological operations in the reproduction step of the GA applied on the selected individuals in order to exploit a priori image information. Tested on gray level images, the presented method has yield good results where objects are well extracted from the background.

***Key words***: Genetic Algorithms, Image Segmentation, Object Extraction, Mathematical Morphology.

# 1. Introduction

Image segmentation is an important task in image processing since it is considered as the primary input to high level vision. Then, the segmentation information is used to interpret and analyze the image contents [7][8].

Many approaches have been proposed to solve the image segmentation problem and we can briefly classify them into: gray level thresholding methods [1], iterative pixel classification [4], Markov random fields [3][6], neural networks [9], etc …

In this paper we propose a contribution to solve the image segmentation problem by using a genetic algorithm associated with mathematical morphology tools in the reproduction step of the GA. Then, the goal of the process is to extract the objects contained in the image from the background.

# 2. The Image Segmentation Approach

The proposed approach of image segmentation is based on genetic algorithms [2]. The main goal is to classify each pixel of the image into pixels belonging either to the object or to the background. We can resume the different steps of the proposed GA as follows.

1. Initialization of the individual population.
2. Evaluation of the fitness function.
3. Choice of the fittest individual to be parents for mating.
4. Reproduction step.
5. Evaluation of the fitness value of the offspring.
6. Selection of the best-bit candidates to form the population of the next generation.
7. Convergence test: if a termination criterion is not satisfied, we iterate from step 3.

To deal with this, we begin first by looking for the space of all binary strings of a fixed length K in a $2^K$ dimensional hyperspace where K is the total number of pixels in the image.

We note that working with a population of solutions instead of a single point, the GA increases the space of search and this permits to reach the looked globally optimum solution and hence the best image segmentation.

## 2.1. Data organization

The first step of any GA is to set the chromosome representation scheme in order to structure the solution. In our work, the entire image is converted to a vector $[x_1\ x_2\ \dots\ x_K]$ where $K$ is the total number of pixels in the image. So the corresponding chromosomes are the $K$ bit string made up from genes representing either intensities of object (Ro) or background (Rb).

The proposed segmentation approach through the GA is applied on the data vector and starts by the population initializing step.

## 2.2. Population Initializing

The initial population is a set of the first generation of individuals in the search space represented by the following sequence:

$\{Y_i^j\}$ where $i$ varies from 1 to $K$ (size of the image) and $j$ varies from 1 to $N$ where $N$ is the population size.

Each $Y_i^j$ represents a gene and also corresponds to a pixel in the image. $Y_i^j$ is randomly chosen to have either the object intensity (Ro) or the background intensity (Rb). We note that each individual from the population is the concatenation of $K$ genes that forms one (01) chromosome.

### 2.3. The fitness function

To select the fittest individuals, we use a fitness function to measure the similarity of each individual with the original image. So let the original image be represented by the following vector $x_i$ where i=1, …, $K$ and the initial population by: $Y_i^j$ where $j$ =1, …, $N$ and $i$ =1,…, $K$. Then, the fitness value $f(Y^j)$ of each individual of the population is computed as follows:

$$f(Y^j) = \frac{1}{\sum_{i=1}^{K} \left| Y_i^j - x_i \right|} \quad j=1, \ldots, N \quad \text{.......} \quad (1)$$

### 2.4. Selection step

The selection step of the GA consists to choose the fittest individuals from the population which will serve as the population in the next generations. In our algorithm, individuals having fitness values greater than a predefined threshold $\phi$ will be selected to be parents in successive operations. The threshold $\phi$ is set as follows:

$$\phi = \frac{Max(f) + Min(f)}{2} \quad \ldots\ldots\ldots\ldots.. \quad (2)$$

where $Max(f)$ and $Min(f)$ are respectively the maximum and the minimum values of fitness of the population.

### 2.5.The reproduction step

This is the key process of any GA. It consists to apply the cross-over and mutation processes on the population. The cross-over operator makes the population to converges around solutions with high fitness. Thus the closer the cross-over probability is to 1, the faster is the convergence. There exists two important types of cross-over: the one site cross-over where a cross-over site is randomly chosen and around which the code chains are exchanged and the uniform cross-over where each gene of the first offspring is randomly chosen between the parents, the gene of the second offspring is complementary with respect to the random choice.

The mutation operation represents the phenomena of rare chance in the evolution process. Indeed, during the process of reproduction, the gene pool may loose some useful genetic material. So the role of the mutation operator is to introduce new genetic material to the gene pool.

#### 2.5.1. Morphological operations

Before applying the cross-over and the mutation process, we propose to perform some morphological operation on the selected individuals in order to exploit connectivity property of the image [5]. The morphological operators used in this work during the reproduction step are "*closing*" followed by "*opening*". The size and the shape of the structuring element have to be chosen with care regarding the desired resolution of the segmentation. Here we use a square structuring element of size 3x3 to favorite the preservation of fine details of objects in the image.

After the morphological operations, the individual are preconditioned and are then subject to the next step of our GA, the cross-over and mutation.

#### 2.5.2. Cross-over

In this step the chromosomes interchange genes in following way:

We affect to each gene a local fitness value $f_i^j = \left| x_i - Y_i^j \right|$ ................ (3)

then the cross-over between two individuals consists to keep all individuals of the first parent which have local fitness greater than the average local fitness $f_{av}^j$ and substitutes the remained genes by the corresponding ones from the second parent. The average local fitness is defined by: $f_{av}^j = \frac{1}{K} \sum_{i=1}^{K} f_i^j$ .................. (4)

#### 2.5.3. Mutation

This step is introduced in order to restore the genetic material lost during different generations, and to improve the fitness values of individuals. It consists to inverse genes that satisfy the mutation probability $\chi$ from each individual. In this paper the value of $\chi$ is fixed at 0.02 .

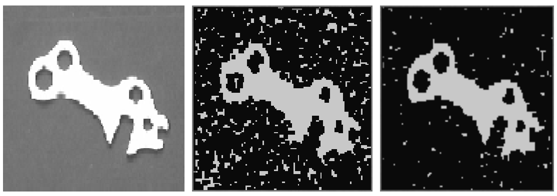
## 3. Results

The segmentation of an image with the presented method consists to extract the pixels of the object on one hand and the pixels of the background in other hand. In our experimentation the intensity of the object (Ro) is set to 200 and the one of the background (Rb) is set to 10 .

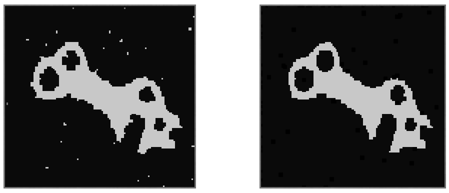
We have applied our method on synthetic images to which we added different kind of noise, and also on gray level images of size 128x128 pixels. The obtained results are satisfying whereas the objects in the images were clearly disconnected from the background.

The termination criterion is reached when the average fitness doesn't change significantly from generation to the next, so the population became uniform and can't give a better solution.

Figure1 shows that larger is the population size, better are the results of segmentation. In this example we see that the segmentation results were improved with a population size of 20 individuals after 20 generations.



original image population size=5 population size=10



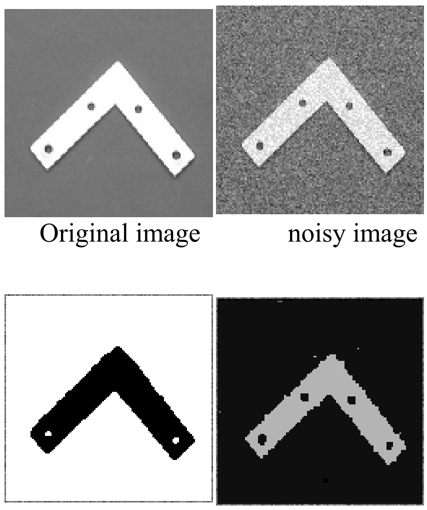
population size = 15 population size = 20

**Figure1**: *Results obtained with different populations size after 20 generations.*

Figure2 shows the results on a noisy image to which we added a gaussian noise of 40 dbp.

As an example of comparison, we show the results obtained with a relaxation-based classification method and the results obtained with our algorithm after 20 generations with population size of 20.

We notice that the result of the relaxation classification method is affected by the noise in the sense that the fine details (the holes) are lost, according to the result obtained with the developed algorithm.



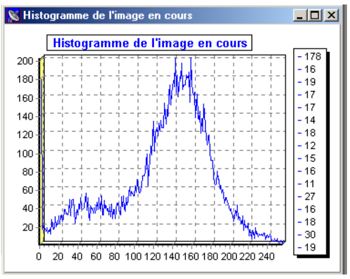
Original image noisy image

Relaxation result GA result

**Figure2**: *Result with a noisy image.*

In the figure3 we show the comparison of our method with the based histogram threshold method, on the outdoor noisy image.

image with gaussian noise of 40 dbp.




The corresponding histogram

According to the histogram of the image we choose the adequate threshold value between 100 and 140 gray level to separate the object from the background, the obtained result is influenced by the noise, when it doesn't a great effect with the proposed method.

## 4. Conclusion:

The method presented in this paper is an unsupervised approach of image segmentation based on a genetic algorithm in conjunction with morphological mathematics. It starts from a random population in which each individual progresses to the same optimal solution which is the segmented image, and achieves, after some generation, by disassociating the objects from the background in the image. The appropriate choice of the shape and the size of structural element has a major effect on the results, and the use of hexagonal once white appropriate size looks promising to improve the results.

## 5. References

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