# Segmentation of textured images by evolutionary approaches

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## *Abstract*

*We present in this article a method of segmentation of textured images based on the extraction of a vector of attributes by the filters of Gabor followed by a classification carried out in the space of these attributes by the method ISODATA (Iterative Self - Organizing Data Analysis Techniques) optimized by genetic algorithms. The method was tested on synthetic images and on satellite images containing natural textures. The obtained experimental results favorably confirm the speed of convergence and the good performance of the proposed algorithm.*

***Keywords:*** *segmentation, texture, genetic algorithm, filter of Gabor*

## 1. Introduction

Image segmentation is an essential step in any image analysis process. It is a low-level processing that precedes the measurement, and decision stage [1]. Its objective is to partition the image into connected and homogeneous regions in the sense of a homogeneity criterion that is difficult to define, especially in the case of textured regions [2][3].

Texture, which is almost ubiquitous in images, therefore plays an important role in image analysis not only in segmentation applications but also in classification and characterization [4][5][6]. Although it has interested many researchers and many works have been published in recent years, the texture continues to arouse the interest of researchers, especially with the success achieved by the wavelet transform and the Gabor filters used in the spatio-frequency analysis of images [7][8].

Haralick's work since 1979 on texture, several approaches have been proposed: statistical, structural, Gabor filter, and wavelet transforms [9].

However, the search for discriminating parameters characterizing the texture and the use of these parameters for the segmentation of textured images still remain a delicate problem, without a universal solution.

It is in this context that we propose in this article a new method of segmentation of textured images. This method is based on a phase of attribute extraction by Gabor filters, characterizing the different textured regions as well as an automatic classification phase of the pixels of the image to be analyzed, by the classification method ISODATA optimized by genetic algorithms.

ISODATA is an unsupervised classification algorithm. Its result depends closely on two parameters: a threshold to split a class and another threshold to merge two classes [10].

A bad choice of these two parameters leads the algorithm to get out of control, leaving only one class in the end. In order to determine these parameters and make improvements to this algorithm, we used genetic algorithms to estimate the two optimal thresholds [11].

This article is structured in sections. The second section presents the state of the art in texture analysis. The third section presents the description of genetic algorithms.

The principle of the ISODATA classification is presented in the fourth section. The fifth section is reserved for the presentation of the genetic algorithm proposed for the segmentation of textured images.

The results obtained by the application of our method on synthetic images and on satellite images presenting natural textures will be presented in the sixth section.

## 2. State of the art on texture

Although the notion of texture is natural for human beings, it has long resisted any attempt at definition. We can approach it by saying that a texture is an area of the image that has certain characteristics of homogeneity that the font appears as a single area.

We can also describe as being a set of primitives of variable size and shape, presenting a particular spatial organization [12].

### 2.1 Texture Types

There are three types of textures: structural textures, random textures and directional textures. Brodatz established a texture catalog for the purpose of textured image synthesis. This catalog is now a reference in terms of a test base for researchers working on texture. There are 112 textures (sand, grass, bubbles, water, wood, etc.) each with sixteen different variations [13]. These images are conventionally used to validate the different texture analysis methods. (Figure1).

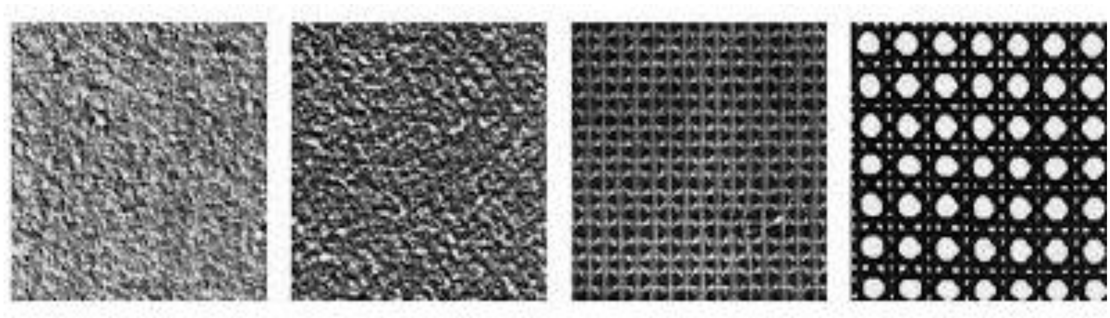

**Figure 1. Examples of textures from Brodatz's album**

### 2.2 Texture analysis

Texture analysis brings together a set of mathematical techniques to quantify the different levels of gray present in an image in order to extract discriminating properties from the appearance of the surface. A wide variety of image texture analysis techniques have been proposed by different authors. These techniques can be categorized into three main approaches:

The statistical approach analyzes the spatial distribution of the gray levels by calculating the local statistics on the values of the gray levels, which are constant or vary very little over a textured region. Different textures can be discriminated by comparing statistics calculated on different sub-regions. These methods are mainly used to characterize fine structures, without apparent regularity [14].

The structural approach models the primitives that make up the texture while characterizing the spatial arrangement rules between these primitives. Indeed, the ordered textures have primitives which are repeated in the images in positions according to a certain law. The structural methods also make it possible to synthesize textures by modifying these rules of arrangement. Such methods seem suitable for the study of periodic or regular textures [15].

The spectral approach which consist of filtering the image using a set of spatial masks in the frequency domain. The texture is considered as a mixture of signals of different frequencies, amplitudes and directions [16]. Spatio-frequency representations preserve both global and local signal information. Textures being quasi-periodic signals having localized frequency energy, these methods therefore make it possible to characterize the texture at different scales. The most used tools are Gabor filters and wavelets.

Gabor filtering is suitable for textures with high periodicity; it requires a careful choice to set the parameters of the filter, in particular the frequency bandwidth and the orientation. After the extraction of textural attributes from the Gabor filter are then integrated into an unsupervised classification procedure based on genetic algorithms. This classification procedure will be detailed in the next section.

## 3. Genetic Algorithms

Genetic algorithms are function optimization methods. These techniques are based on the evolution of a population of solutions which, under the action of precise rules, optimize a given behavior, expressed in the form of a function, called a selective function (or objective function).

A genetic algorithm manipulates a population of constant size. This population is made up of candidate points called chromosomes. Each chromosome represents the coding of a potential solution to the problem. It is made up of a set of elements called genes. The latter are real numbers.

At each generation, a new population is created from the previous one by applying genetic operators which are: crossing, mutation and selection. The two operators of crossover and mutation change the chromosomes (parents) of the population in order to produce new chromosomes (son) allowing to optimize the selective function [17]. These procedures allow the algorithm to avoid local optima. The selection operator consists in constructing the population of the next generation which will be constituted by the relevant individuals. Figure 2 illustrates the different steps involved in a standard genetic algorithm.

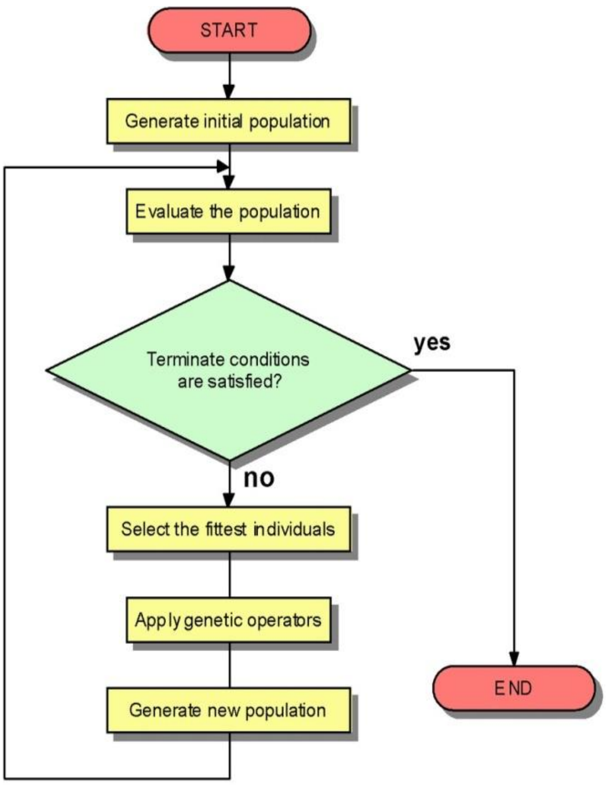


**Figure 2. Standard genetic algorithm**

## 4. ISODATA classification

It is an improved version of the k-means algorithm, this algorithm, named "Iterative Self-Organizing Data Analysis Technics" ISODATA, allows, during iterations, merging between clouds nearby, high-variance cloud splitting, and small-sized cloud suppression.

This method calculates the averages of N classes, regularly distributed in the data space by successive iterations. It will assign the remaining observations to cluster centers based on their minimum distance. At each iteration, the means are therefore recalculated; the observations are reclassified according to the new means [18].

This calculation continues until the rate of observations changing in each class is below the threshold set by the user or the maximum number of iterations is reached.
Thus, a new range of mean vectors is calculated from the previous iteration allowing a reclassification of the observations.

ISODATA generally gives a good statistical division of the spectral space with low intra-class inertia. The user must therefore specify the following parameters [19]:

- The minimum number of observations in any class.
- The maximum standard deviation, when in a class, this deviation is exceeded and the number of observations is twice greater than the specified minimum of observations, the class is split into two classes.
- The minimum distance between class centers. Classes with a weighted distance less than this value will be merged.

Consider a set of $M$ objects $\{O_1, O_2, ..., O_i , ..., O_M\}$ characterized by $N$ attributes grouped as a row vector $V = (a_1\ a_2\ ...\ a_j\ ...\ a_N)$.

Let $R_i = (a_i)\ 1 \le j \le N$, be a row vector of $\boldsymbol{R^N}$ whose j^th^ component $a_{ij}$ is the value taken by the attribute $a_j$ on the object $O_i$.

Let *matr_obs* be the matrix of $M$ rows (representing the objects $O_i$) and $N$ columns (representing the attributes $a_j$), defined by:

$$matr_{obs} = (a_{ij})\ \ 1 \le i \le M\,; 1 \le j \le N \qquad (1)$$

We call $V$ attribute vector, $R_i$ the observation associated with the object $O_i$ or realization of the attribute vector $V$ for this object, $\boldsymbol{R^N}$ the observation space and *matr_obs* observation matrix associated with $V$. The th line of *matr_obs* is the observation $R_i$ belongs to a class $CL$ s, s=1, …, C.

From a geometric point of view, if each observation is represented by a point in the observation space $\boldsymbol{R^N}$, the set of observations then constitutes a cloud of points in this space.
In this work, we are more interested in the last two parameters.

Figure 3 presents the Isodata algorithm:

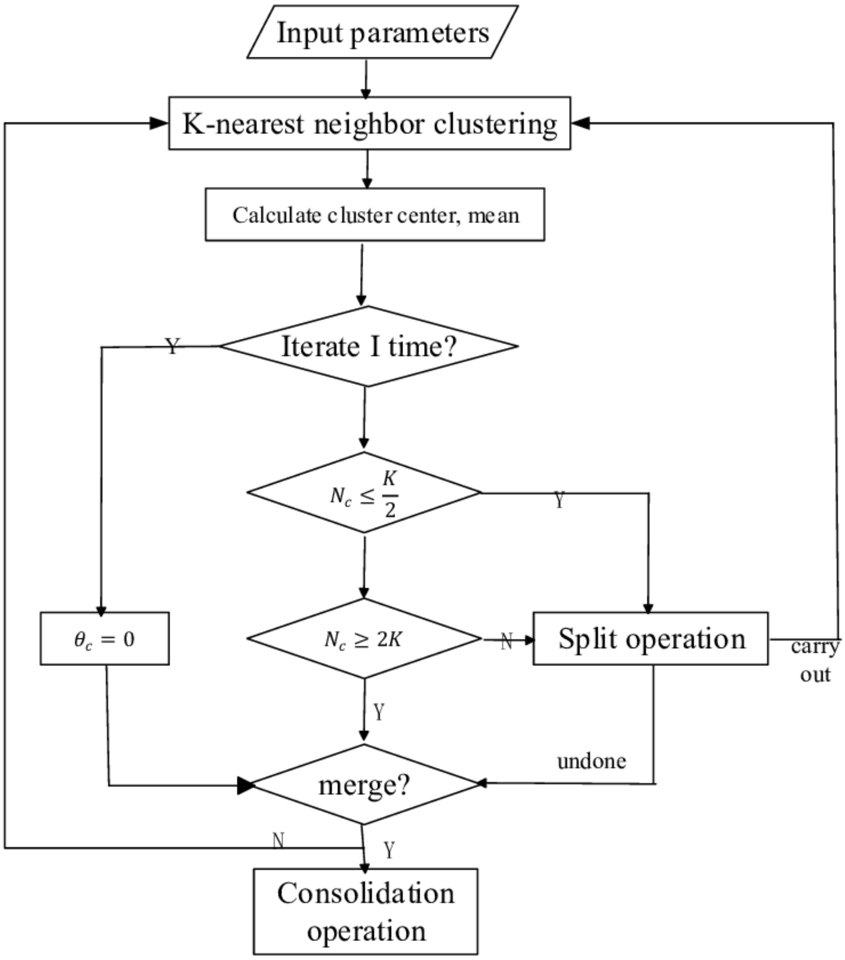


**Figure 3. ISODATA algorithm flow chart**

## 5. Proposed method

Our method has two main phases: the extraction of attributes by Gabor filter and the unsupervised classification by ISODATA optimized by genetic algorithms.

### 5.1 Textural analysis based on Gabor filters

Gabor filters are introduced by Dennis Gabor in 1946. These filters have been widely used both as wavelet decomposition functions and as textural analysis tools.

A Gabor filter is a Gaussian function modulated by a complex sinusoid. In the spatial domain, a Gabor filter H(x, y) is defined as follows:

$$h(x,y) = \frac{1}{2\pi\sigma^2} exp\left[-\frac{(x^2+y^2)}{2\sigma^2}\right] exp\big(j2\pi F(x\cos\theta + y\sin\theta)\big) \qquad (2)$$

$\sigma^2$ determine the spatial extent of the filter. In the frequency domain, after the Fourier transform of H(x,y), the Gabor filter is a Gaussian surface centered on the frequency $F$ and the orientation $\theta$:

$$H(u,v) = exp[-2\pi^2\sigma^2((u - F\cos\theta)^2 + (v - F\sin\theta)^2)] \qquad (3)$$

The parameters that define each of the filters are therefore the frequency $F$ and the orientation $\theta$ around which the filter is centered in the frequency domain and the standard deviation $\sigma$ of the Gaussian [20].

In 2D, the Gabor filter is defined by a two-dimensional Gaussian modulated by a plane sinusoidal function.

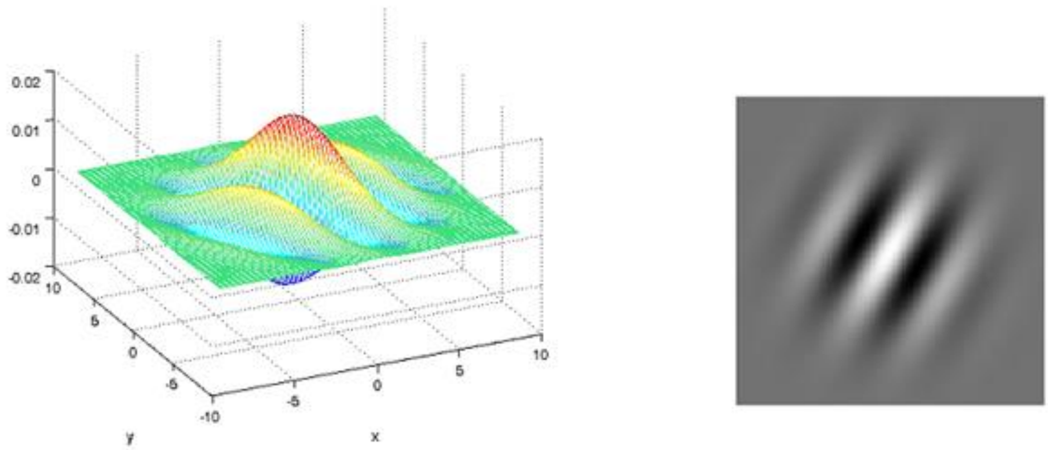


**Figure 4. Impulse response of a 2D Gabor filter with σx = σy = 3, $f_0$ = 0.25 and θ = π/6**

## 5.2 Proposed AG-ISODATA Algorithm

### 5.2.1 Coding

The proposed algorithm consists in selecting among all the possible partitions the optimal partition by minimizing a criterion. This leads to determine the parameters ($p_s$), $1 \leq s \leq np$. Thus we propose the following real coding:

$$chrom \; = (P_s) \;\; 1 \leq s \leq np \qquad (4)$$

$$= P_1, P_2, P_3, \dots\dots\dots . P_{np}$$

The chromosome is a real row vector of dimension $np$. The genes (ps), $1 \leq s \leq np$ are the components of chrom. To avoid initial solutions that are very far from the optimal solution, each chromosome of the initial population must satisfy the following condition:

$$P_s \; \in [minp, maxp]$$

We must delete during the iterations of the genetic algorithm any chromosome of the population having a gene not respecting this constraint. This gene is replaced by another satisfying the constraint.

### 5.2.2 Selective function

Unlike K-means which obliges to give the number of classes a priori, ISODATA itself determines the number of classes not exceeding a maximum chosen beforehand and which appears among the parameters that the user must provide.

We were inspired by this behavior of the ISODATA algorithm to choose the selective function. Indeed, the reiteration of this algorithm several times and with parameters generated automatically by the genetic algorithm will lead to the optimal number of classes, this is our objective. For this purpose, we have retained the well-known criterion of Xie and Beni. The latter is based on a measure of compactness and separability of classes [21][22].

The compactness criterion measures the concentration of observations around their center, defined by:

$$Comp = \frac{1}{M}\sum_{i=1}^{M}\sum_{s=1}^{C}\|R_i - g_s\|^2 \qquad (5)$$

The separability criterion measures the distances between centers of observations, defined by:

$$Sép = min_{s\neq s'}\|g_s - g_{s'}\|^2 \qquad (6)$$

Let chrom be a population chromosome formed by the parameters ($ps$), $1\leq s\leq C$. to calculate the selective value of chrom we define the following selective function F:

$$F(chrom) = \frac{Comp}{Sép} \qquad (7)$$

With: chrom is optimal if F is minimal.

### 5.2.3 Crossover and mutation operators

The performance of a genetic algorithm is judged according to the crossover and mutation operators used. For the crossover operator, we opted for the arithmetic mean of the 2 parent individuals on each of their parameters. Indeed, if we have two chromosomes:

$$chrom \ = (P_s) \quad 1 \leq s \leq np \qquad (8)$$

$$chrom' = (P'_s) \quad 1 \leq s \leq np \qquad (9)$$

The crossing is between the first and each of the chromosomes of the population. Regarding the mutation operator, the one proposed in the literature is given by the following expression:

$$chrom^{*} = chrom + \sigma \times N(0,1) \qquad (10)$$

Where *chrom** represents the new chromosome produced by the Gaussian perturbation of the chromosome *chrom*. *N(0,1)* is a Gaussian with mean 0 and variance 1 (normal distribution with mean 0 and variance 1) generated for chromosome *chrom*. $\sigma$ is called strategic parameter.

Unlike evolution strategies which are based on the mutation operator, genetic algorithms are rather based on the crossover operator. This is why the mutation only takes place on a parameter with a probability fixed at P*mut*. We will set P*mut* to 0.1, i.e. a parameter with a 10% chance of mutating.

To choose the chromosomes (parents) of the population that will be mutated to generate other chromosomes (son), we adopted the technique of choice by ranking.

1. **To stare**

   The population size ***maxpop***.
   The maximum number of generation ***maxgen***
   The maximum number of classes ***C***

2. **Randomly generate population *P***

   ***P*** = {*chrom1*, .., *chromk*, ..., *chrom maxpop*}

3. **Check for each *chrom* of P the constraint**

   $P_s \in [minp, maxp]$

4. **Repeat**

   ISODATA for each *chrom* of ***P***
   Compute the selective value for each *chrom* of ***P***
   Ranking of *chroms* in ascending order of their selective values
   Cross the first *chrom* with all the others
   Randomly generate the constant **σ** (σ ∈ [0.5, 1]).
   Mutation of all chrom of ***P*** except the first
   Check for each chrom of ***P*** the constraint: $P_s \in [minp, maxp]$
   The population P obtained constitutes the population of the next generation

   **Until** (Number of generation) > ***maxgen***

5. **Retain the optimal *chrom*: the first of the last *P***

6. **ISODATA for optimal *chrom***

**Figure 5. Proposed AG-ISODATA algorithm**

## 6. Experimental Results and Discussion

We tested our method on a synthetic image containing 3 regions then on satellite images containing 5 classes with natural textures. These tests were carried out by textural descriptors issued by Gabor filter and an evolutionary classification AG-ISODATA.

In order to obtain the best optimization results by the AG-ISODATA algorithm, the selection of parameter values is important because these parameters can seriously affect the performance of this algorithm.

After several tests, the size of the population and the maximum number of iterations are fixed at 20 and 50 respectively.

Other parameters such as dimension were considered for the objective function. In our work, the objective function to be optimized is the intra-class inertia also called the quadratic error function since we used the Euclidean distance as a measure of similarity and the stopping criterion is the maximum number of iterations.

### 6.1 Synthetic image

We first tested our algorithm on the image of figure 6 which is coded on 256 gray levels. It contains three homogeneous regions of different sizes and shapes.

The texture descriptor (figure 7) was calculated from the Gabor filter. After several tests, the size of the sliding window was fixed at 7 x 7, Sigma=10, Angle=1.21 and frequency=10.

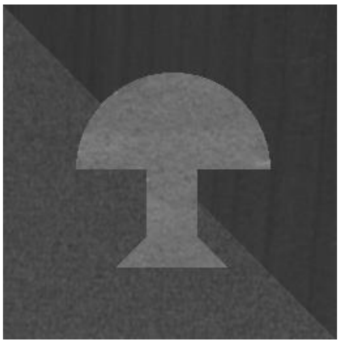

Figure 6. Synthetic image used

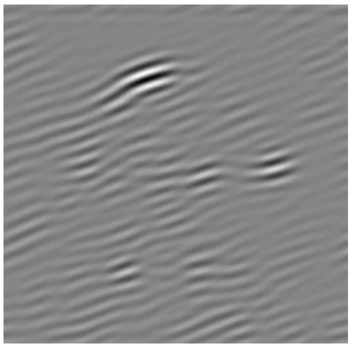

Figure 7. Textural descriptor issued by Gabor filter

For the synthetic image used, the parameters of AG-ISODATA were fixed after several tests as follows: the size of the Population =20; number of iteration =50, probability of mutation =0.1. The segmentation result presented in Figure 8 and Figure 9.

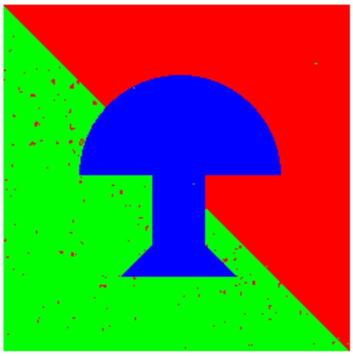

Figure 8.Segmented image by AG-ISODATA

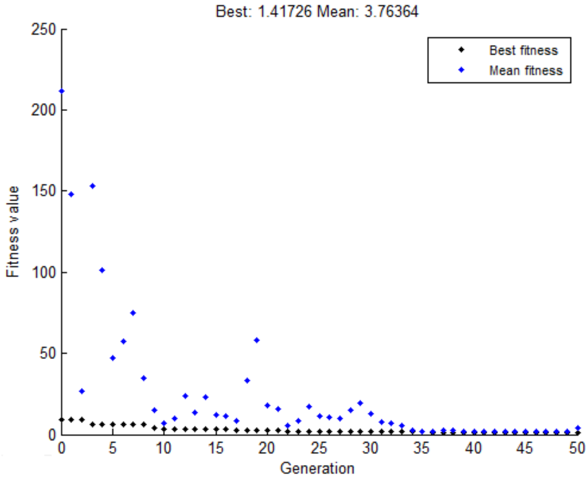


Figure 9.variation of the fitness value

For the dimension, we used an image coded in RGB (Red Green Blue) where the individual is a vector of three elements (d = 3) of real numbers with a textural descriptor issued by Gabor filter which gives the dimension 4 ( D=4).

Figure 8 and 9 show that the AG-ISODATA algorithm associated with the texture descriptors calculated by Gabor filter recognized exactly the number of clusters (classes) according to the number of classes constituting the original image (k = 3) with a global minimum which equals 1.41726 .

### 6.2 Satellite images

The procedures of our classification were tested on the digitized data of the LANDSAT 5 -TM satellite images, of the region of Mostaganem north of Algeria acquired on August 2, 2009 of 400 x 400 pixels with a spatial resolution of 30 meters (Figure10).

The studied area is known by the diversity of the terrain, the presence of several themes and the problems of confusion between the different classes, which represents an ideal platform to test the effectiveness of our approach.

Confusions appear on the image because of the shadow effect and some different themes with similar spectral responses. This situation is of great interest for the test of the contribution of textural information during the classification tests carried out. This image contains five main themes: urban, vegetation, water, bare ground and fallow.

The texture descriptor (figure 11) was calculated from the Gabor filter. After several tests, the size of the sliding window was fixed at 51 x 51, Sigma=10, Angle=0.61 and frequency=30.

**Figure 10. Satellite image used**

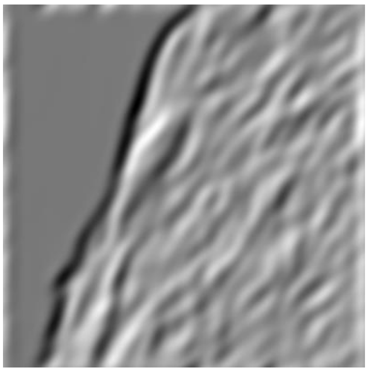

**Figure 11. Textural descriptor issued by Gabor filter**

The segmentation result presented in figure 10 and figure 11 shows that the AG-ISODATA algorithm associated with the texture descriptor recognized exactly the number of clusters (classes) existing in the image.

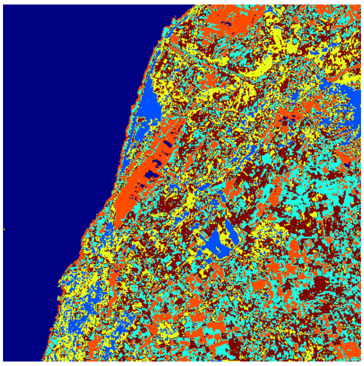

**Figure 10.Segmented image by AG-ISODATA**

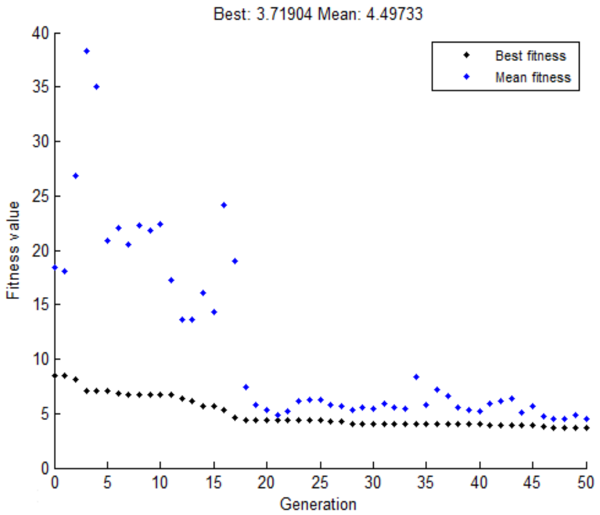


**Figure 11.variation of the fitness value**

The objective of this experiment was to measure the performance of the proposed AG-ISODATA algorithm for the unsupervised classification of satellite images. The purpose of this part is to show the interest of minimizing the quadratic error as an objective function optimized by the AG-ISODATA algorithm. Figure 10 and 11 show that the AG-ISODATA algorithm is associated with the texture descriptors calculated by Gabor filter recognized exactly the number of clusters (classes) according to the number of classes constituting the original image ( k = 5) with a global minimum which equals 3.71904 . In order to evaluate the presented approach, the results are compared to the real surface (because this area is known). These images show that the quality of the unsupervised classification by AG-ISODATA algorithm allows better visual recognition using texture descriptors.

At this level (Table 1), we will compare the evolutionary algorithm AG-ISODATA in terms of values of global minima recorded according to the various tests carried out and in terms of execution times.

**Table 1: Comparison of AG-ISODATA in terms of execution time and global minimum**

| **AG-ISODATA Parameters**: Population Size =20; Number of iteration =50, Mutation probability =0.1 | | |
|---|---|---|
| Synthetic image | | Satellite image |
| **Global Minimum** | 1.41726 | 3.71904 |
| **Execution Time** | 4.895 s | 13.577 s |

By comparing the dimension of the synthetic images studied previously (256x256), we find that the execution time is lower compared to a real scene of spatial dimension (400 x 400), having 3 spectral bands and 1 textural band. This depends on the dimension of the search space and on the dimension of the image studied.

## 7. Conclusion

We presented in this paper a segmentation method of textured images based on the extraction of attributes by Gabor filter and the classification of attributes by the AG-ISODATA method. We can conclude that our contribution to integrate textural information with spectral information to improve the quality of the classification.

The unsupervised classification by the ISODATA algorithm presents the difficulty of adjusting its parameters. We have proposed a new approach to overcome this difficulty of the ISODATA algorithm. This approach is based on genetic algorithms. We have proposed the crossover and mutation operators to allow the algorithm to avoid local solutions and to converge to the global solution in a small number of generations. Gabor's filter texture analysis presents a fairly robust tool for characterizing textures and its conjunction with the evolutionary classification method AG-ISODATA provides a fairly reliable segmentation method.

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