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Contextual fusion by genetic approach applied to the classification of satellite images

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ABSTRACT: Contextual fusion consists of the combination of multisource and multitemporal data by taking into account the information given by spatial or temporal context. In this paper, we propose a contextual fusion process for satellite image classification based on genetic concept. A Genetic Algorithm (GA) seeks the extreme of a function defined on data space called "initial population". Each individual of this population is a chromosome characterised by a whole of genes. Genetic programming uses this data structure and makes evolve iteratively the initial population through a specific number of generations by successively applying three genetic operators : selection, crossover and mutation. Searched solution is a final population obtained when a termination criterion is satisfied. To develop our contextual fusion process based on a genetic approach we have used two GA. The first one is applied during the training step to extract a data base of best chromosomes where each best chromosome characterises one information class. The second one is applied for the classification of each chromosome (pixel) taken in its spatial neighbourhood. Test data set available is TM5 multispectral image of Algiers city (Algeria). This image acquired in 1996, contains nine main classes illustrated in two thematic maps; one given by a genetic approach and the other by a Markovian approach. A comparative study is then carried out between these two approaches.

1 INTRODUCTION

Conventional classification techniques, both supervised and non-supervised, are used for the classification of remote sensing data on the basis of spectral signature of pixels. This type of classification leads to misclassification and is limited to improving classification accuracy. In a practical situation, the response and class of two spatially neighbouring pixels are highly related. The decision for a pixel therefore is taken based not only on its spectral signature but also on all its neighbouring pixels spectral signature. In this way, spatial information or "context" is incorporated in classification. The goal of such techniques called "contextual classification" is to obtain more classification efficiency and accuracy in remote sensing applications. Different supervised methods have been evolved to introduce context in classification. Unfortunately, the most robust methods create an optimisation problem due to the explosion of combinations in the search space. To solve this problem, Bayesian statistical theory which has been widely used as a theoretically robust foundation for satellite image non contextual classification has been already adapted by our research team (Khedam *et al.,* 2001), (Khedam *et al.,* 2002). So, to maximise the posterior probability (MAP), it is necessary to model both class conditional and prior probabilities. The prior probability density function (pdf) is often assumed gaussian. However, prior information is very difficult to model. Using context concept to model this information is generally accepted as a reasonable procedure and has been introduced by S. Geman and D. Geman (1984) for image restoration and by J. Besag (1986) for filtering dirty images. Discrete random field models, especially Gibbs random field (GRF) and Markov random field (MRF), have been found to be a useful tool for characterising contextual information. The parameters of gaussian distribution are learnt from training samples. The pixels of the image are then iteratively classified following ICM algorithm by calculating, from their observed response, the likelihood that they have come from different classes. In this paper, we shall describe another solution to the optimisation problem based on principles of natural genetics

and evolution. It uses Genetic Algorithm (GA) which is a search and optimisation method developed by mimicking the evolutionary principles and chromosomal processing in natural genetics. A GA begins its search with a random set of solutions usually coded in binary string structures. Every solution is assigned a fitness function which is directly related to the objective function of the search and optimisation problem. Thereafter, the population of solutions is modified to a new population by applying three operators similar to natural genetic operators: reproduction, crossover, and mutation. A GA works iteratively by successively applying these three operators in each generation till a termination criterion is satisfied. Over the past decade, GA have been successfully applied to a wide variety of problems, because of their simplicity, global perspective, and inherent parallel processing (Deb, 1998). In our case, we apply an adaptive GA to classify contextually remote sensed data. This paper is organised as follows. In the next section, we present a genetic approach and outline the working principle of a GA by describing the three genetic operators. Thereafter, we show in section III how to apply a GA to solve a contextual fusion problem of remotely sensed data. Experimental results of both Markovian and genetic approaches applied on real multispectral data, are provided and compared in section IV. Finally, a discussion and conclusions are given in section V.

2 GENETIC APPROACH

The genetic algorithm technique has been described by Goldberg (1994) as an important and a robust research theme. It has also been presented by Deb (1998) as a potential search and optimisation method to solve a number of different complex problems. The GA was first conceived by Professor J. Holland of University of Michigan, Ann Arbor in 1965. His first book appeared in 1975 and till 1985, GAs have been practiced mainly by Holland and his students. Exponentially a greater number of researchers and practitioners became interested in GAs soon after the first International Conference on GAs held in 1985. Now, there exist a number of books (Goldberg, 1989; Mitchell, 1996) and a few journals dedicated to publishing research papers on the topic (including one from MIT Press and one from IEEE) (Deb, 1998). The major reason for GA's popularity in various search and optimisation problems is its global perspective, widespread applicability, and inherent parallelism. A genetic algorithm is an abstraction of the complex natural genetic and natural selection process. It is an iterative optimisation procedure that works with a complete set of population domain. The size of the population determines the size of the sampling space with larger population sizes affording a better possibility of finding the optimal solution but the procedure becomes computationally expensive. The domain of the population will comprise a number of *individuals*. These individuals are essentially concatenated strings or arrays representing a set of design variables. Each design variable representation forming part of an individual string or array is known as a *chromosome*. A flowchart of the working principle of a simple GA is shown in Figure 1.

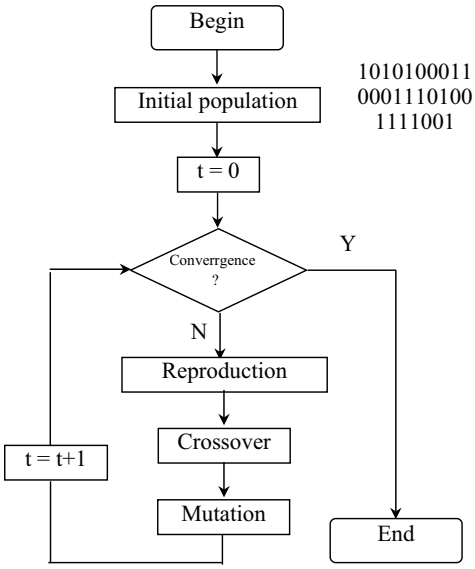

Figure 1. A flowchart of GA's principle

A GA begins its search from a random population of solutions. As shown in figure 1, a solution in a GA is represented using a string coding of fixed length defined according to each optimisation problem. If a termination criterion called convergence criterion is not satisfied, three different operators : reproduction, crossover, and mutation are applied to update the population of strings. One iteration of these three operators is known as a *generation*. The final population represent the searched solution.

2.1 *Selection - Reproduction*

Reproduction is usually the first operator applied on a population. Reproduction selects good strings in a population and forms a mating pool. There are a number of selection-reproduction operators in GA literature (Goldberg, 1989), (Deb, 1998). We can find the proportionate selection operator and a ranking selection scheme. Recently, some new operators appear. "N/2 élitisme", the "tournoi" selection and the "roulette de Wheel" are getting popular because of their simplicity and controlled take-over property (Michalewicz *et al.,* 1996).

2.2 *Crossover*

Crossover operator is applied next to the strings of the mating pool. Two strings are picked from the mating pool at random and some portion of the strings are exchanged between the strings. In a single-point crossover operator, both strings are cut at an arbitrary place and the right-side portion of both strings are swapped among themselves to create two new strings, as shown in the following figure:

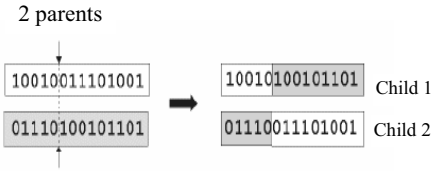

Figure 2. Single-point crossover operator

2.3 *Mutation*

Mutation operator changes a 1 to a 0 and vice versa with a small mutation probability. The need for mutation is to maintain diversity in the population. A mutation operator is illustrated in the following figure :

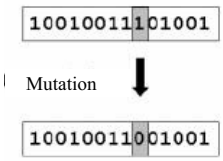

Figure 3. Mutation operator

After reproduction, crossover, and mutation are applied to the whole population, one generation of a GA is completed. These three operators are simple and straightforward. Reproduction operator selects good strings and crossover operator recombines good sub-strings from two good strings together to hopefully form a better string. Mutation operator alters a string locally to hopefully create a better string. For more details about GA in search and optimisation (the techniques and applications), see (Deb, 1998). We now discuss how to apply a GA to solve our contextual fusion optimisation problem.

3 CONTEXTUAL FUSION OF REMOTELY SENSED DATA

Remotely sensed data have proved to be of great interest for land cover classification and for detecting and mapping of land cover changes. For a particular remote sensing application, image data might be available from several different sensors and in different time periods. In addition, other sources of information, in particular some computer databases like the Geographic Information System (GIS), prove to be very useful as well. Automatic or semi-automatic analysis of this important data mass has become an important task in image processing. A data fusion process has been proposed as a formal framework in which are expressed means and tools for the alliance of data originating from different sources. It aims at obtaining information of greater quality; the exact definition of "greater quality" will depend upon the application. (Wald, 1999). In our application, the task is to combine available data to improve classification accuracy. An alternative of a common statistical approach based on Bayes theory and MRF, is to use an adapted genetic approach for satellite data.

3.1 *Adapted genetic approach*

The application of a genetic approach aims to search an optimal labelled image from an initial population of chromosomes. Each chromosome represents the multispectral response of a pixel being of the set of pixels for the whole scene. It can also represent multisource and multitemporal measurements of a pixel. Unlike the Markovian approach where training samples are extracted and selected directly according to *a priori* information based on ground truth, in a genetic approach a first GA is applied to these samples to choose the best chromosomes. Each best chromosome characterises one information class. The whole of the best chromosomes constructs a robust training database. A second GA is applied for each pixel or chromosome to classify considering in its spatial context which can be its eight neighbours pixels. The adapted genetic approach for image classification is illustrated by figure 4.

3.1.1 *Initial population*

The size of initial population determines the size of the sampling space with larger population sizes affording a better possibility of finding the optimal solution but the procedure becomes computationally expensive.

3.1.2 *Chromosomes representation*

The coding of chromosomes consists in finding a form of individuals' representation, usable by our algorithm. There are several types of coding, for our part, we used binary coding, because of its adaptation to the genetic operators, namely the crossover and the mutation operators. Indeed, the individuals are represented by binary strings. The size of chromosomes is proportional to the size of research space which is the class size and also the whole of the pixels located in the selected trainings zones. Therefore the research space is equal to :

Size of the class = $\sum_{i=1}^{m}$ (Xbi - Xhi)*(Ybi - Yhi),

with (Xh, Yh) the higher top coordinates, and (Xb, Yb) are the lower top of the extracted zones coordinated, m is a number of samples of a given class. The size of chromosomes is then equal to:

$$L = Log_2(\text{size of the class})$$

If for example for a space of research equalizes to 511, then $L=Log_2(511) = 9$ (size of chromosome), then chromosome 000000000 corresponds to the first pixel of first sample of the class, and chromosome 111111111 corresponds to the last pixel of the last same sample.

3.1.3 *Fitness function*

It is a real positive value which evaluates chromosomes. In our method the function fitness of a unit (chromosome) is the calculation of a number of the frequency of appearance of this unit in the considered class. Our goal is to find the best chromosome which characterizes the treated class. The function fitness is a function to maximise. So, the fitness function must search the chromosome that has a significant repetition number of its radiometric value in all the spectral channels.

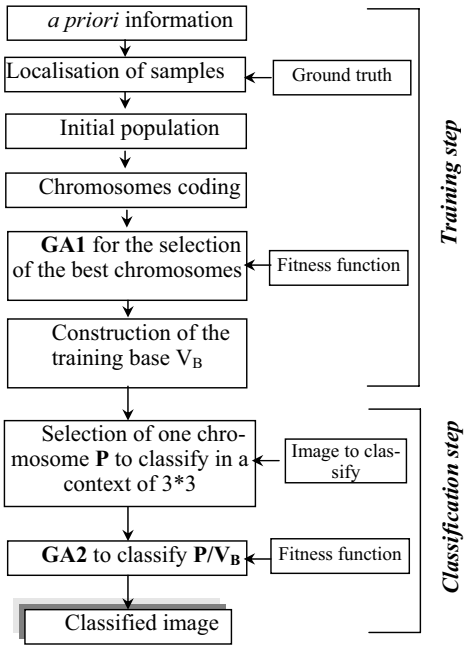

Figure 4. GA approach for image classification

3.2 *Training step*

In supervised mode, construction of a training data base is very important and has a direct influence on the final classification result. Using a GA, this base is constructed as follows:

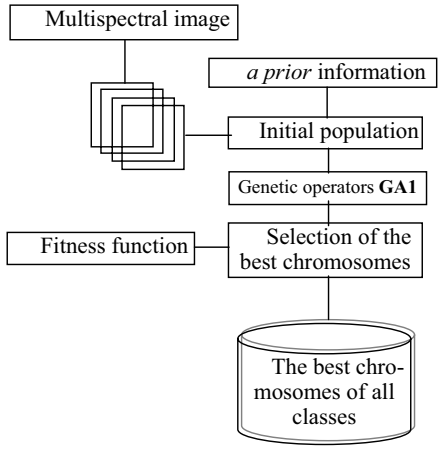

Figure 5. Training step

1. Initial population has generally a size of 30 to 100 individuals. Then it will be randomly generated and this is one of the most important GA advantages. In this way, initial population is not homogeneous and is distributed in all research fields.
2. Clustering all pixels that are supposed to belong to each class defined from the ground truth. The result set is called "initial population".
3. Coding the initial population. This means that each individual will contain a series of substructures or genes. In our case we chose a binary code to represent each individual from the population.
4. Fitness function is a real positive value to evaluate chromosomes. In our case, we have considered fitness function of a unit as the appearance frequency of this unit in a considered class.
5. Genetic operators: a new generation is constructed using the process of reproduction, crossover and mutation. Reproduction means that individuals are randomly selected from the existing population, weighted by the individual's performance (success) in terms of the fitness function. Crossover involves exchange of genes between individuals. Mutation involves the random flipping of bits (0/1, 1/0) within an individual's coding.

3.3 *Classification step*

Spectral channels are represented in a multidimensional space. We use a minimum Euclidean distance as a similarity measure between a pixel to classify and a selected chromosome in the training data base. So, our task becomes the minimisation of a fitness function representing the Euclidean distance.

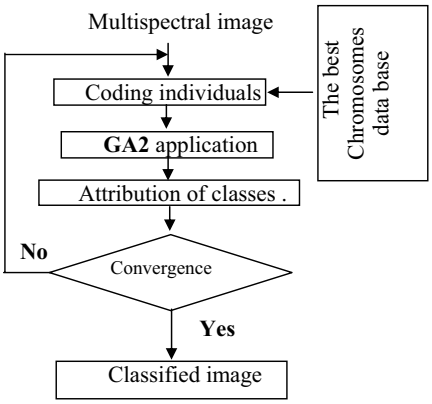

Figure 6. Classification step

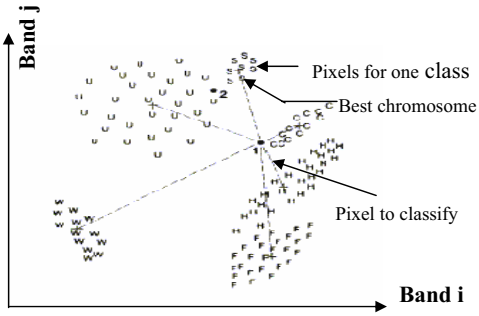

Figure 7. Classification space

4 EXPERIMENTAL RESULTS

We have tested both the ICM algorithm and GA on a LANDSAT TM image acquired on 1996. It consists of six spectral bands covering Algiers bay located in the north of Algeria. We have defined on this image of size 400x400 (see figure 8), nine discriminating classes as shown in this table:

Class	Object
1	Landing strip of Algiers airport
2	Less dense urban area
3	water
4	Less dense agricultural area
5	Cultivate agricultural area
6	Corn field
7	Roads
8	Dense urban area
9	Dense agricultural area

Figure 8. Classes of test image

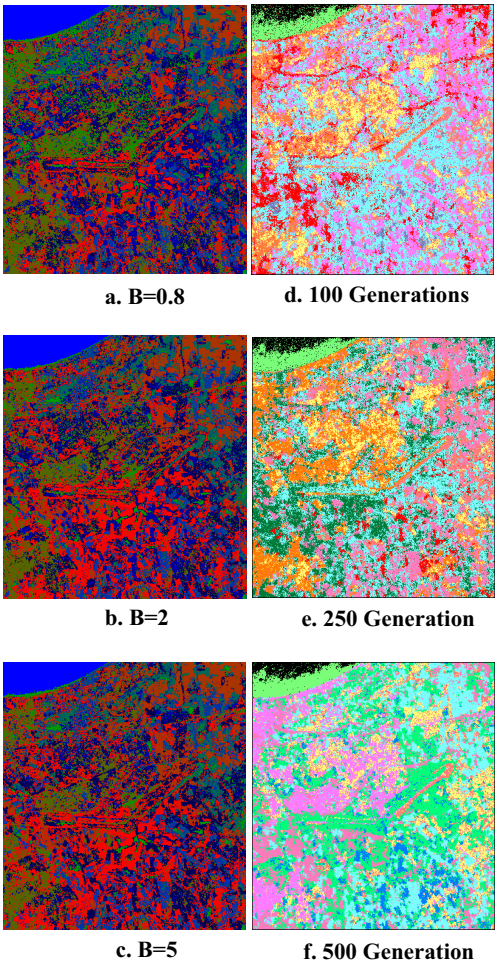

Figure 9.

Classification results using Markovian and genetic approaches are given on figure 9. In the framework of images MRF modelling, different optimisation algorithms have been suggested to minimise a specific energy function. Simulated annealing (Marroquin *et al.,* 1987) can be used to release this minimisation but is computationally very demanding and we therefore prefer to use the Iterated Conditional Modes (ICM) algorithm (Khedam *et al.*, 2002) instead. These two algorithms have the same basic idea. However, they differ in that the first converges to the global maximum of the posterior distribution, while the latter converges in a short time to the local maximum. ICM is an iterative process: at each site s the current class label is updated given all available information. Then, a right choice is the class label that has the maximum conditional probability which is equivalent to the minimum of energy function. ICM algorithm is considered as a regularisation process of an initial labelled configuration. The regularisation is operated through Potts model which is a function of regularisation parameter β and a neighbourhood topology adopted in the image (4-connexity or 8-connexity). This relaxation technique is fast, but strongly depends on the initial configuration and regularisation parameters. For more details about ICM algorithm see (Jhung *et al.,* 1996), (Khedam *et al.,* 2001).

When comparing the results for ICM algorithm and genetic algorithm, it might seem strange that the improvements in accuracy due to the use of spatial context with both Markov and genetic theories are very similar. In the first results set (figure 9, a, b and c), parameter β weighted regularisation term. So, greater homogeneous areas are obtained for high β values and low β values act slightly on regularisation of homogeneous areas. From $\beta=0.5$, the regularisation is more significant and becomes strongly significant beyond $\beta=2$. However, when observing the classified images for these values, we realise that, outwards training samples, strong regularisation degrades some linear structures and destroys some small pieces. Optimal β value is, so selected empirically according to a visual appreciation of obtained results. This value should produce a trade-off between the preservation of fine structural details and the smoothing of homogeneous regions (Khedam *et al.,* 2002). We observe the same phenomena in the second results set. The regularisation process is performing with a higher generation number. Note that the sea pollution phenomena is carried out on these results but not on the first results which is very important when studying a detection dynamic change.

5 CONCLUSION

Punctual classification has often a "salt and pepper" appearance due to misclassification. Thus, the obtained thematic map is inadequate to describe ground cover types. To cure this problem, contextual classification based on a genetic approach which exploits the correlation between spatially adjacent pixels, is presented in this paper and is compared with an ICM algorithm based on Bayes theory and MRF. These two approaches are search and optimisation methods developed by mimicking a particular natural phenomenon and are drastically different in principle from the classical methods like direct and gradient based methods (Deb, 1998). Genetic approach is developed by analogy with the evolutionary principles and chromosomal processing of natural genetics and natural selection. However, the Markovian approach is based on simulated annealing operation observed in statistical physics. Through our study, we have proven that the approaches are very similar.

Both of them operate contextually on the image to produce an optimal thematic map. The two approaches can be combined to perform a classification result.

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