Supervised images classification using metaheuristics

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Abstract

Image classification is a fundamental task in image processing because it is a crucial step toward image understanding. This paper exploits metaheuristics (Ant Colony Optimization and Electromagnetic Metaheuristic) to tackle the problem of supervised satellite image classification. Earlier studies have been used the Intra-Class Variance (ICV) for images classification but this function has a limits to solve classification problem. This study presents the introduction of the Davies-Bouldin Index (DBI) to the supervised images classification. This index is used in two stages: training step and classification step. In training step this index serve as criteria for controlling iterations. In the classification step this index help to classify each pixel in the image to their appropriate class using the class centers found during the training stage. The experimental results show that the introduction of the Davies-Boulin index is very effective for supervised images classification and help the community of researches to improve the classification accuracy of remotely sensed data. The utility of metaheuristics is also demonstrated for satellite image of Oran city.

Keywords:

image classification
metaheuristics
Davies-Bouldin index
ant colony optimization
electromagnetic metaheuristic.

1 Introduction

Remote sensing image classification is a preliminary step in computer vision applications. This processing is extensively used for agricultural planning and crop monitoring, providing a basis for decision-making [1]. The goal of this classification is to decompose an image into meaningful or spatially coherent regions sharing similar attributes [2]. A vast majority of classification techniques are supervised, which requires that the number of classes and the class distribution model to be known in advance. Unsupervised classification divides all pixels within an image into corresponding classes and proceeds with fewer interactions with the analyst. A lot of classification approaches have been proposed and applied to multispectral remote sensing images. 1) mathematical techniques: Support Vector Machine [3], Maximum Likelihood [4], K-means clustering [5], Bayesian Classifier [6] and Independent Components Analysis [7]. 2) bio-inspired techniques: different types of Neural Networks such as the Multilayer Perceptron [8], the Radial Basic Function Network [9] and the Kohonen Network [10]. Another example of algorithms inspired from biology: Genetic Algorithms [11, 12] and Artificial Immune Systems [13].

The aim of this research is to develop a repeatable, accurate meta-heuristic method to classify remote sensing imagery. This paper focuses mainly on integrating ACO [14] with different objective functions and comparing the different results. The utility of ACOs in solving problems that are large, multimodal and highly complex has been demonstrated in several areas [15-19].

It is known that the quality of the classification result using optimization technique depends wholly on the objective function performances. The ICV value has been used as objective function in several works [20 - 21]. This function requires that each class data approximately follow a normal distribution. To avoid this drawback, we have introduced DBI [22] to supervised classification. The DBI value depends both on the distance between class center and simples and on the distance between class's centers. This Index has been used for unsupervised remote sensing images classification in several works [12, 23, 24].

Finally, to evaluate the performance of DBI function on supervised remote sensing image classification, the ACO based classifier results were compared with those from another metaheuristic called Electromagnetic Metaheuristic (EM) [25].

This article is organized in the following ways: in the second section (methodology) we illustrate the ant colony optimization, coding and objective functions. The third section is devoted to the presentation of the study area and the experimental results. A conclusion and perspectives are presented in section four.

2 Methodology

2.1 ANT COLONY OPTIMIZATION

The ACO is a paradigm for designing metaheuristic algorithms for complex optimization problems. These algorithms can be regarded as a multi-agent system where each agent is functioning independently by very simple rules [26]. In this paper we are interesting to use API algorithm [27] for land cover classification. The API algorithm is based on natural behavior of *pachycondyla apicalis* ant. The API base algorithm is different from the basic ACO in terms of search strategy; in the process of foraging ants communicate with each other using visual landmarks rather than pheromone.

2.1.1. Pachycondyla apicalis behavior

This colony has been studied in Mexican tropical forest near Guatemalan border [28]. The behavior of such colony can be characterized as follows:

- The ants create their hunting sites around the nest within a radius of approximately 10m.
- The ants will intensify their search around some selected sites for prey capture.
- Each time a prey is found, it is brought back to the nest and the next ant's exit will focus on this profitable hunting site.
- When a hunting site impoverishes, the ant has a tendency to explore other hunting sites.
- When the nest is starting to be unhealthy, scant ants are searching from a new nest location.

2.1.2. Behavior modelling

The modeling behavior of the ant Pachycondyla apicalis is proposed by Monmarché et al. [26]. It corresponds to an algorithm called API, which is designed to solve optimization problems. The explored space by the ants is transformed to a search space noted by S (Fig.1, 2). The nest, ants and hunting sites are represented by points (location) on S.

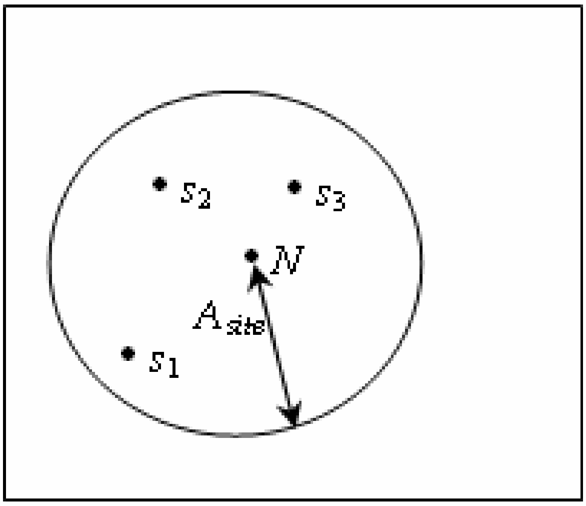


FIGURE 1 Creation of the hunting sites (s_1, s_2, s_3) around the nest N respecting amplitude A_{site}

Initially the nest (N) is uniformly generated in the search space (Figure 1) using equation (1). Afterward, each ant of the population (n ants) generates p hunting sites around the nest (Figure 1) by using equation 2 and by respecting an amplitude Asite. An ant explores a site of hunting using equation (2) by respecting an amplitude Alocale (Figure 2) during Plocale representing the number of successive failures in a hunting site. A failure means that an ant changed its location in the search space without improving the objective function.

The global goal of the population is to minimize a function during a number of iterations noted T. The ant tries to find s' in the neighborhood of s, such that f(s') is better than f(s). This is the modeling of the capture of the prey.

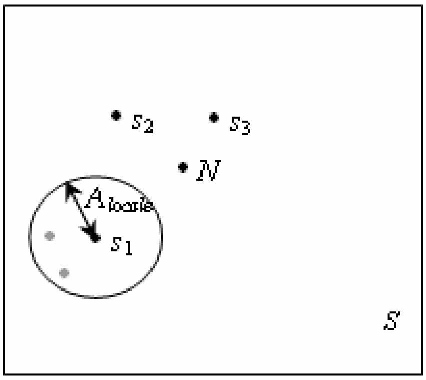


FIGURE 2 Exploring the hunting site s_1 respecting amplitude A_{locale}

The most important elements in the API algorithm are the exploration operators. The first operator (equation (1)) generates randomly a point s in the search space S:

$S = [b_1, B_1][b_2, B_2]\ldots[b_l, B_l]$; l: is the dimension of the objective function. $s = (s_i)\ S\ ; i = 1, 2, \ldots, l$.

$$s_i = b_i + U[0,1](B_i - b_i) \quad (1)$$

$U[a,b]$: a uniformly random number in the interval $[a,b]$.

The second operator (equation 2) generates a point s' in the neighborhood of s by respecting an amplitude A. The amplitude A is equal to A_{site} during the creation of the hunting site and it's equal to A_{locale} during the exploration of the hunting site.

$$s_i' = s_i + AU[0,1](B_i - b_i) \quad (2)$$

2.1.3.API algorithm

Choose randomly the initial nest location
While (T<Number of iteration) do
For each ant
Create p hunting sites
While (patience<P_{locale}) do
Explore hunting site
End while
End for
If the nest must be moved, then move the nest to the best ant's coordinates
End while

2.2. CODING AND OBJECTIVE FUNCTION

There are several steps to establish an API classifier for supervised remote sensing image classification, including encoding ant's strings, definition of the objective function, and executing the API algorithm operators.

2.2.1. Ant coding

In ACO applications, the parameters of the search space are encoded in the form of string, so-called ants, representing a solution of problems. In this paper, an ant is encoded with units of positive integer numbers; each unit represents a class center. Take the following case as an example.

Assuming we have a satellite image with three bands, considering the four class' centers of the ant in the population is as shown in Figure 3.

15	148	230	0
2	35	3	7
212	92	64	9
C_1	C_2	C_3	C_4

FIGURE 3 Structure of an ant in API algorithm

2.2.2. Objective function

Starting from initial solution (nest position) selected randomly, API algorithm preserve the appropriate solution based on an objective function which is associated with each ant that represents the degree of goodness of the solution encoded in it.

Two validity indices have been used in this paper, the first is the Intra-class Variance (ICV), and the second is the Davies-Bouldin Index (DBI).

Several classification validity indices have been developed to determine an optimal classification, for example the Separation Index, "SI", the Davies-Bouldin "DB" index and the Xie-Beni Index, "XBI" [22].

The within class variance value has been used in several researches [29, 20, 21].

$$IV = \sum_{i=1}^{k} \sum_{x \in X_k} \left(x_j - C_i \right). \tag{3}$$

The DBI has both a statistical and geometric rationale. The API algorithm adopts the DBI as objective function due to its suitability for remote sensing imagery [23, 24, 30, 31, 12]. The DBI can be calculated as follows:

$$\mu_{ki} = \begin{Bmatrix} 1; & \arg\min\limits_{1<j\le n} \left\| x_i, C_j \right\| = k \\ 0; & otherwise \end{Bmatrix}, \tag{4}$$

where:

x_i: The gray level of pixel *i*.

M_k: Number of elements in class *k*.

u_{ki}: Membership function of pixel *i* to class *k*.

X_k: All elements of class *k*.

Then the average (v_i) and standard deviation (S_i) of each class are calculated as follows:

$$v_k = \frac{\sum_{i=1}^{M_k} (\mu_{ki}) x_i}{\sum_{i=1}^{M_k} (\mu_{ki})} = \frac{\sum_{x_i \in X_k} x_i}{M_k}, \tag{5}$$

$$S_k = \left(\frac{1}{M_k} \sum_{x \in X_k} \left\| x - v_k \right\|^2 \right)^{1/2}. \tag{6}$$

Now calculate the distance between the averages' classes:

$$d_{kj} = \left\| v_k - v_j \right\|_t, \tag{7}$$

d_{kj} is the Minkowski distance of order t between the k^{th} center and the ith center.We set t=2.

Then the R_k value of k^{th} center is calculated by equation.

$$R_k = \max_{j, j \ne k} \left\{ \frac{S_k + S_j}{d_{kj}} \right\}. \tag{8}$$

The DB value is defined as the average *R* of all classes.

$$DB = \frac{1}{n} \sum_{k=1}^{n} R_k. \tag{9}$$

3 Experimental results

3.1 STUDY AREA

A satellite Landsat TM7 image of the Oran area, Algeria acquired on April 22, 2003 is used for the experiment of classification using API algorithm. The study area consists of 400×800 pixels with a ground resolution of 30 m (Fig. 4). This area is dominated by the following eight land use types: sea (C1), surf (C2), sand (C3), forest (C4), cereals (C5), burning (C6), fallow (C7) and urban (C8). Based on the field investigation and land-use maps, samples (pixels) are acquired. The sample data set is further divided into two groups, i.e., 1/3 as training data set and 2/3 as test data set.

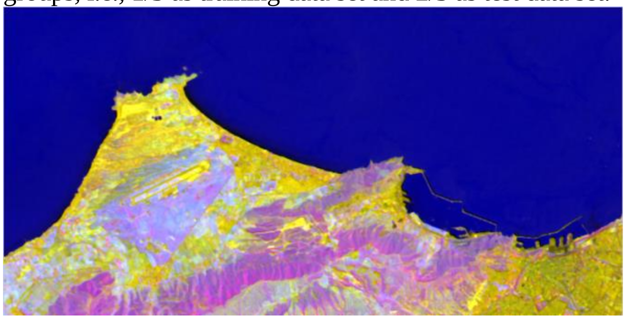


FIGURE 4 Oran TM image

3.2 TRAINING STEP

To achieve a good classification result, it is necessary to minimize the DBI value. A minimum DBI value is the averaged optimal ratio of the intra class scatter over the inter class separation. In our work the u_{ki} is not used because the training class samples are known a priori. In the following example we explain how we have used the DBI index and the ICV value as objective functions for supervised satellite images classification.

$A_1 = (1, 2, 3, 4), A_2 = (5, 6, 7, 8), A_3 = (9, 10, 11, 12).$

We add an element (integer number) in each class samples and subsequently we calculate the BDI value. This operation is summarized in Table 1.

TABLE 1 Search of the class centers using DBI

Test	Class 1	Class 2	Class 3	DBI value
1	$A_1 \cup \{3.5\}$	$A_2 \cup \{8\}$	$A_3 \cup \{12.5\}$	0.5802
2	$A_1 \cup \{3\}$	$A_2 \cup \{7.5\}$	$A_3 \cup \{12\}$	0.5352
3	$A_1 \cup \{2.5\}$	$A_2 \cup \{7\}$	$A_3 \cup \{11.5\}$	0.5051
4	$A_1 \cup \{2\}$	$A_2 \cup \{6.5\}$	$A_3 \cup \{11\}$	0.4926

In Table 1 we found that the minimum of DBI value is obtained when the elements 2.5, 4.5 and 6.5 are added to the class A_1, A_2 and A_3 respectively. It is also noted that the DBI value minimizes when the added values are close as in test 4. The DBI value becomes minimal when not only the added elements are the classes' centers, but also when they are distant between them.

TABLE 2 Search of the class centers using ICV value

Test	Class 1	Class 2	Class 3	ICV value
1	4	6	8	6
2	3.5	5.5	7.5	5
3	3	5	7	4
4	2.5	4.5	6.5	4
5	2	4	6	4

We propose to put the elements added in Table 1 as class' centers of A_1, A_2, A_3 and then we calculate the Euclidean distance (ED) between the classes' centers and the items of each class. This is summarized in Table 2.

In table 2 the minimum ICV value is repeated in several tests. Tests 3 and 5 have the same ICV value of test 4 (optimal class centers). We can say that the results are not guaranteed when using ICV as an objective function.

3.3 CLASSIFICATION STEP

Classifications using the Euclidean distance as objective function presents always limits because given items will not going allocate necessarily to the appropriate class. Figure 5 below shows a real example of our problem where the items will be classify to the small class because it is closer to the class center of this class; however it is more appropriate that it will be classify to the big class (Figure 5).

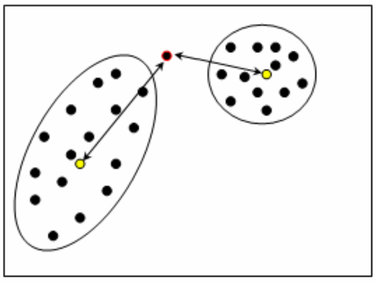


FIGURE 5 Classification problem

In this work we apply two objective functions: ICV and DBI for the classification stage. For the ICV function the principle is simple; simply allocate the pixel that we want to classify to the class where the class center is the closest. For the DBI function, we add the pixel to be classified to the training samples of a given class, and we add in the other class' samples the optimum class centers found during the training stage and subsequently we calculate the DB value. This procedure is repeated for each class. The pixel is thus allocated to the class where the DB value is minimal. Our principle of classification is summarized in Table 3.

Suppose we have the learning sample E_1, E_2, E_3 of three classes.

$$E_1 = \{1,\ 2,\ 3,\ 4\}; E_2 = \{5.5,\ 6,\ 6,\ 6.5\}, E_3 = \{9,\ 10,\ 11,\ 12\}$$

The classes centers found during learning using the DBI function are: 2, 6, 11. Our problem is to affect the item 8 in the appropriate class.

TABLE 3 classification using DBI

E_1	E_2	E_3	DB value
$E_1 \cup \{8\}$	$E_2 \cup \{6\}$	$E_3 \cup \{11\}$	0.9227
$E_1 \cup \{2\}$	$E_2 \cup \{8\}$	$E_3 \cup \{11\}$	0.4625
$E_1 \cup \{2\}$	$E_2 \cup \{6\}$	$E_3 \cup \{8\}$	0.4121

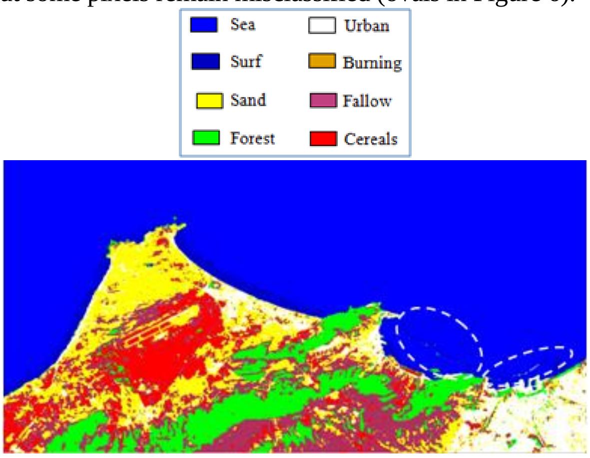
In Table 3 the minimum value of DB was obtained when we added the item 8 in the training sample of the class 3, thus this item will be allocated to Class 3. By contrast, if we use the ICV function, the item 8 will be allocated to the class 2 because it is so close to the class center of this class.

3.4 CLASSIFICATION OF THE STUDY AREA

The API algorithm has a number of parameters to be determined in advance. After several tests the algorithm parameters are fixed as the following: $n = 10$, $p = 40$; $A_{site} = 20$; $A_{locale} = 5$; $P_{locale} = 10$; $T = 5$.

We note API-DBI and API-ICV when using BDI and ICV as objective functions respectively.

In Figure 6 and 7 we can notice a small difference between the results of both approaches. The API-ICV method was able to distinguish the eight classes of the study area, but some pixels remain misclassified (ovals in Figure 6).



FIUGRE 6 Classification using API-ICV

The API-ICV approach produces confusion because some pixels of the urban class were classified in to the surf class (two ovals in Figure 6). Visually API-DBI method has produced a better classification. In Figure 7 the confusion has been reduced.

To make a quantitative comparison between the results, we examine the confusion matrix, the overall accuracy and the Kappa coefficient. Table 4 and 5 shows the confusion matrix of API-ICV and API-DBI. The first technique produced an overlapping between several classes.

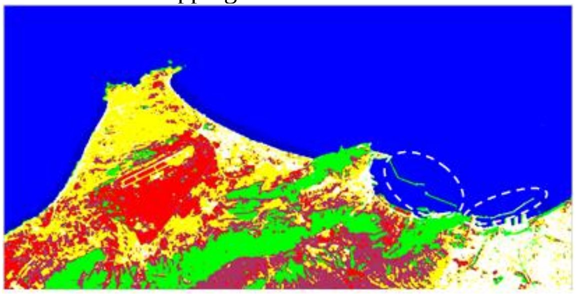


FIGURE 7 Classification using API-DBI

The most important overlapping made between sand class and cereals one, because the pixels of the sand class were recognized as pixels of the cereal class. This approach has also allocated pixels of the urban class to the forest class.

TABLE 4 Confusion matrix of API-ICV

	C_1	C_2	C_3	C_4	C_5	C_6	C_7	C_8
C_1	**100**	0	0	0	0	0	0	0
C_2	2.5	**97.5**	0	0	0	0	0	0
C_3	0	0	**80**	0	12.5	0	0	7.5
C_4	0	0	0	**97.5**	0	2.5	0	0
C_5	2.5	0	2.5	0	**90**	0	0	5
C_6	0	0	0	2.5	0	**92.5**	5	0
C_7	0	0	0	5	0	0	**95**	0
C_8	0	10	0	0	2.5	0	0	**87.5**

The API-DBI method makes a good classification but there is a small confusion between cereals and sea classes and between sand and urban classes. Table 6 shows that the API-DBI technique produces a good overall accuracy, that is to say a high percentage of pixels well classify. We note an increase in the classification rate from 92,50% for API-ICV to 94,68% for API-DBI thus an improvement of 2.18%. It is recognized that the classification rate is not enough to know the performance of a given technique [32]. To measure this performance, we used furthermore the Kappa Coefficient. Table 6 shows that the Kappa coefficient increased from 0.9246 for API-ICV to 0.9466 API-DBI, so an improvement of 0.022.

TABLE 5 confusion matrix of API-DBI

	C_1	C_2	C_3	C_4	C_5	C_6	C_7	C_8
C_1	**97.5**	0	0	2.5	0	0	0	0
C_2	2.5	**97.5**	0	0	0	0	0	0
C_3	0	0	**87.5**	0	7.5	0	0	5
C_4	0	0	0	**97.5**	0	2.5	0	0
C_5	2.5	0	2.5	0	**87.5**	0	0	7.5
C_6	0	0	0	5	0	**90**	5	0
C_7	0	0	0	5	0	0	**100**	0
C_8	0	0	0	0	0	0	0	**100**

To measure the quality of the new objective function we used a second metaheuristic inspired by the attraction and repulsion of electric charges [25]. This method called Electromagnetic Metaheuristic (EM), have been applied to various problems such as: production systems of the type Hybrid Flow Shop [33], scheduling projects [34], scheduling nurses [35] and solving nonlinear systems of equations [36]. We have used EM algorithm for classification of the study area. For more details about the EM algorithm refer to Birbil et al., [25]. We note EM-ICV when we use the ICV function, and we note EM-DBI when we using the DBI function. The EM algorithm parameters are set as following: $LsIter = 10$ (number of iterations in the local search), $m = 100$ (number of particles), $MaxIteration = 10$; $\delta = 0.05$;

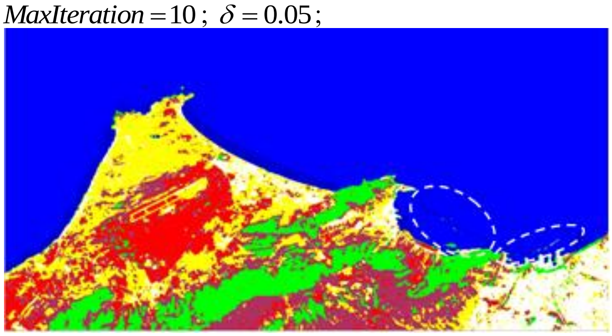


FIGURE 8 Classification using EM-ICV

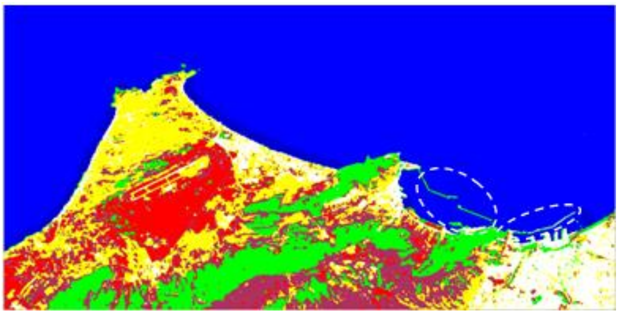


FIGURE 9 FIGURE Classification using EM-DBI

Visually the results obtained by EM algorithm are the same of those of the API algorithm (Figure 8, 9). The DBI confirm its performance on remote sensing images classify-cation. The EM-DBI classifies better than EM-ICV because in this approach pixels in the urban class are classified to the surf class. The EM-DBI produces a good classification; all classes are distinct without apparent great confusion.

Table 7, 8 shows the confusion matrix of the EM-ICV and EM-DBI approaches. The first method produces con-fusion between all classes except sea class. EM-DBI was able to improve the classification except a small confusion between the sand and cereals classes and between cereals and urban classes.

TABLE 7 confusion matrix of EM-ICV

	C_1	C_2	C_3	C_4	C_5	C_6	C_7	C_8
C_1	**100**	0	0	0	0	0	0	0
C_2	2.5	**97.5**	0	0	0	0	0	0
C_3	0	0	**77.5**	0	15	0	0	7.5
C_4	0	0	0	**97.5**	0	2.5	0	0
C_5	2.5	0	2.5	0	**92.5**	0	0	2.5
C_6	0	0	0	2.5	0	**92.5**	5	0
C_7	0	0	0	2.5	0	0	**97.5**	0
C_8	0	10	0	0	2.5	0	0	**87.5**

TABLE 8 Confusion matrix of EM-DBI

	C_1	C_2	C_3	C_4	C_5	C_6	C_7	C_8
C_1	**97.5**	0	0	0	0	0	0	0
C_2	2.5	**97.5**	0	0	0	0	0	0
C_3	0	0	**87.5**	0	7.5	0	0	5
C_4	0	0	0	**97.5**	0	2.5	0	0
C_5	2.5	0	2.5	0	**87.5**	0	0	7.5
C_6	0	0	0	5	0	**90**	5	0
C_7	0	0	0	0	0	0	**100**	0
C_8	0	0	0	0	0	0	0	**100**

We recorded an overall accuracy equal to 92.81% for EM-ICV and 94,68% for EM-DBI thus an increase of 1,87%. The Kappa coefficient was also improved from 0.9277 for EM-ICV to 0.9466 for EM-DBI.

4 Conclusion

The metaheuristic in fact complex multi-agent system in which agents with simple intelligence can complete complex tasks trough cooperation. Two metaheuristics (API, EM) have been applied to the classification of remote sensing image of Oran, Algeria. The comparison of classification result is carried out between DBI and ICV objective functions.

The overall accuracy on using ICV is 92.50% and 92.81% for API and EM respectively. The API-DBI and EM-DBI have an accuracy of 94.65 and 94.68 respectively. In this paper, DBI has been successfully introduced to supervised satellite image classification; however, there is still some limitation on using metaheuristics on remote sensing images classification problem. On the one hand, the DBI Objective function makes much longer time than ICV function during the training stage. On the other hand, the large number of parameters and the difficulty of their choices stand as major obstacles for the use of the metaheuristics (API, EM) for remote sensing images classification. As perspective, would not fix the parameters of the metaheuristics but to make it dynamic. Another perspective is to introduce the communication concept between ants during the exploration step. The last perspective is to use a robust local search algorithm.

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