Conception of the Sflavar Approach: Classification of Satellite Data

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ABSTRACT

Unsupervised classification is the search for homogeneous groups in a dataset. This problem is therefore of great complexity and the use of approximation algorithms is inevitable. In this regard, we will call upon a system resulting from a vision of collective intelligence inspired by the behavior of frogs as individuals seeking food, collaborating with each other to accomplish tasks that they cannot perform individually. As a measure of optimization we will make a change by integrating other variation operators. This will be applied to a LANDSAT5 TM (Thematic Mapper) satellite image of the ORAN region.

Key words: Bio-inspiration, Frog jump algorithm, Satellite image, Unsupervised classification, Variation operators.

1. INTRODUCTION

Off the planet, satellites observe our environment. The measurements they record are sent to ground stations; there computers use the information to provide us with images of how the earth works. Specialists can study ozone concentration, wind circulation or the temperature of the atmosphere and oceans. Artificial colors allow bettering distinguishing the movements of the sea the state of the forests or the ripening of the crops, Henceforth no region is inaccessible [1].

These observations will be transformed into images called satellite images, which allow us to watch over the health of the planet will constitute a gigantic knowledge and a new treasure that must be exploited.

Today, satellite images are becoming an essential tool for monitoring, planning and forecasting, but their analysis and processing requires the use of robust and powerful methods.

Many methods have been designed, now metaheuristics are considered more efficient and more suitable for this field and more precisely bio inspired methods [2].

The latter are inspired by biology such as genetic algorithms, artificial immune systems [3], neural networks [4][5]; either ethology such as fly algorithm [6], particle swarms [7], ant algorithm [8]

In this paper, we looked at the frog jump algorithm where the population looks for localities that have a maximum amount of food randomly spread on stones in a pond [9], thus we propose to make changes to this algorithm

2. FROG JUMP ALGORITHM

When This algorithm is a metaheuristic method of bioinspired optimization where Each Frog, represents a solution to the problem(Figure 1). The entire frog population is divided into a number of groups of frogs called communities that evolve independently to travel the space of solutions in different directions.   Information between different communities flows through a jumping process [10]-[12].
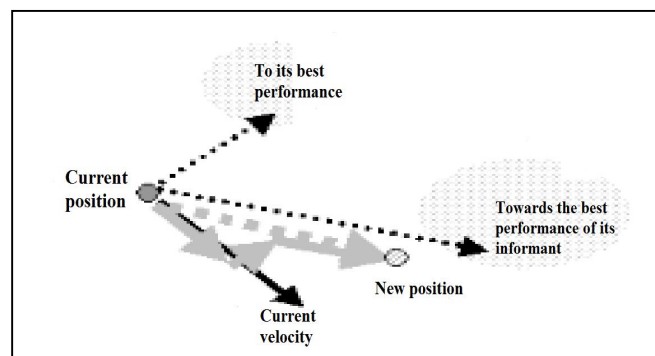

Figure 1: Diagram of principle of frog movement

Suppose the initial population, consisting of μ frogs, randomly defined in space ($i = 1,2, \ldots , \mu$).

The fitness $f(i)$ of the Ith frog represents the value of the objective function. All frogs are sorted in descending order and are divided into m communities each containing n frogs ($\mu=m\times n$), so that the first frog belongs to the first community, the second frog is assigned to the second community etc.

In each community, the frogs providing the best X_b and the worst solution X_w.

The frog giving the best solution in the entire population is noted by X_g.

During the evolution of a community, (local exploration), the worst frog makes a jump to the best X_b based on the following rules [13]:

$$S = R \times X_b - X_w \qquad (1)$$

$$X_{w'} = X_w + S\,(S < S_{max}) \qquad (2)$$

Where

S : the value of the jump,
R : a random number between 0 and 1,
S_m : the maximum allowable jump.

If the jump improves the solution, then this X'_w replaces the worst X_w. Otherwise, the same rule is applied by replacing this X_b by X_g.

If X'_w is still worse than X, then we randomly generate another solution better than X_w and replace X_w with X'_w. Each community evolves in a number of iterations.

The m communities are then mixed to re-form the population and the sorting process, partitioning the population into communities, local research and the mixing of communities is repeated until a stop criterion is met (maximum iteration number reached) [14] [15].

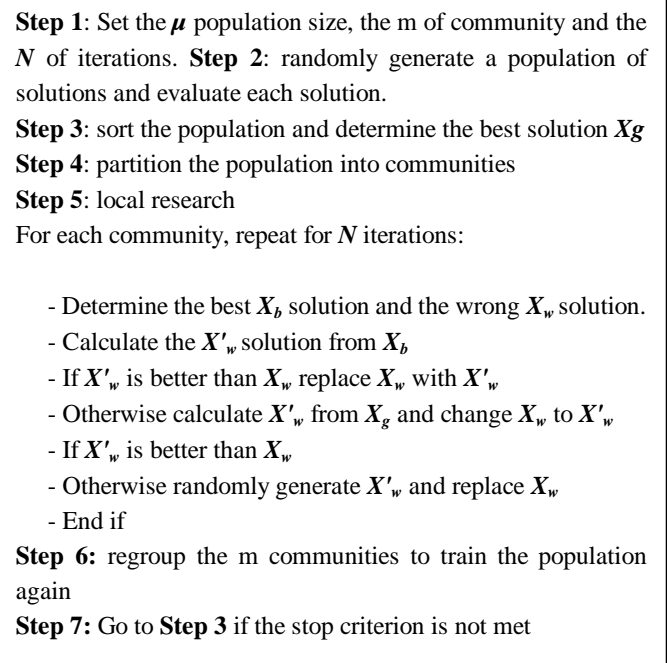The steps of the SFLA algorithm are illustrated by the Figure 2:

Step 1: Set the μ population size, the m of community and the N of iterations. **Step 2**: randomly generate a population of solutions and evaluate each solution.
Step 3: sort the population and determine the best solution Xg
Step 4: partition the population into communities
Step 5: local research
For each community, repeat for N iterations:

    - Determine the best X_b solution and the wrong X_w solution.
    - Calculate the X'_w solution from X_b
    - If X'_w is better than X_w replace X_w with X'_w
    - Otherwise calculate X'_w from X_g and change X_w to X'_w
    - If X'_w is better than X_w
    - Otherwise randomly generate X'_w and replace X_w
    - End if
Step 6: regroup the m communities to train the population again
Step 7: Go to **Step 3** if the stop criterion is not met

Figure 2: SFLA algorithm

3. VARIATION OPERATORS USED

Frogs can improve by communicating with each other (by passing information), which is not always verified and can lead to divergence, the reason why we used the evolutionary algorithm variation operators (crossing, mutation and migration) which are considered more efficient [4][16].

3.1 Crossing

Because It is important to note that the method of crossing chosen depends on the representation of individuals (in our work the representation is real). Thus, to calculate the new individuals (children) Pβ it is enough to choose a cut-off point (that is to say a position in the chain) from which the data are exchanged between the two parents.

3.2 Mutation

The mutation is the second variation operator used just after the crossing. It consists in modifying the individuals resulting from the crossing.

In the case of a real representation, the simplest way is to add to each individual component a realization of a centered normal law (of zero expectation and standard deviation set by the user).

3.3 Migration

Use Migration involves introducing a predefined number of new randomly created Pγ individuals into the current population to ensure population diversity.

4. SFLAVAR APPROACH DIAGRAM

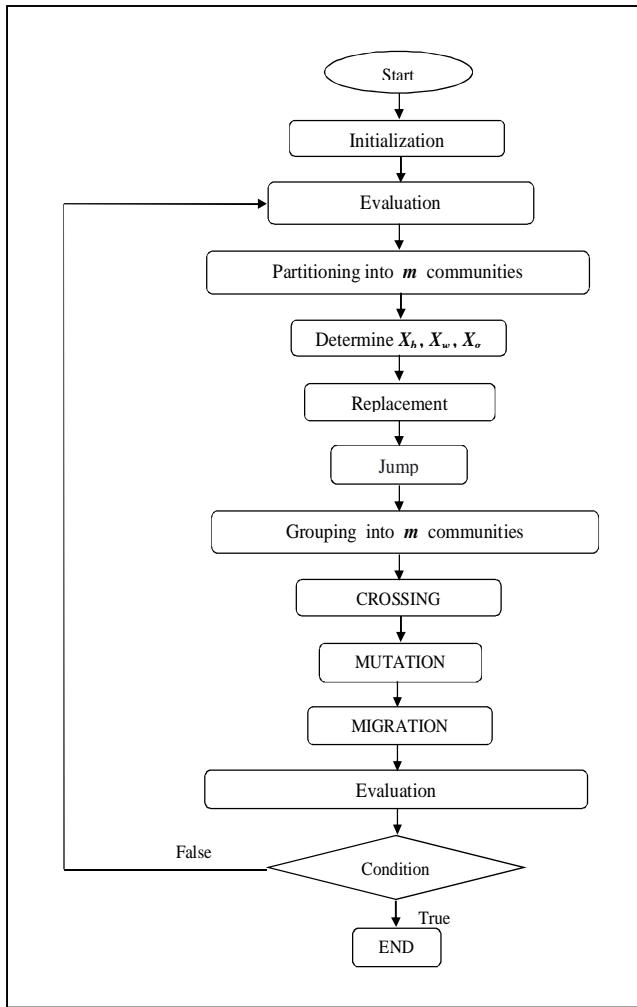The diagram of the SFLAvar approach is as follows (Figure3):

Figure 3: Diagram of SFLAvar

5. APPLICATION OF THE SFLAVAR APPROACH TO SATELLITE IMAGE CLASSIFICATION

We will apply our SFLAvar approach to the unsupervised classification of a synthetic image and a satellite image of type LANDSAT5 sensor TM (Thematic Mapper) taken in 2010. The images used are shown in Figure 4 above.
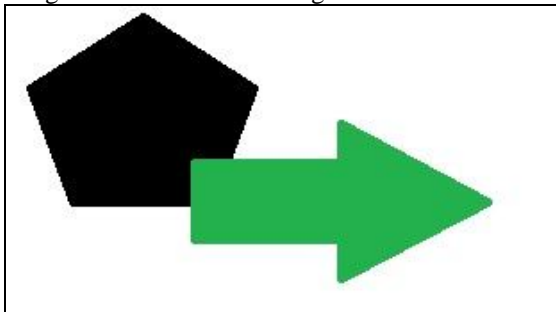
(a)
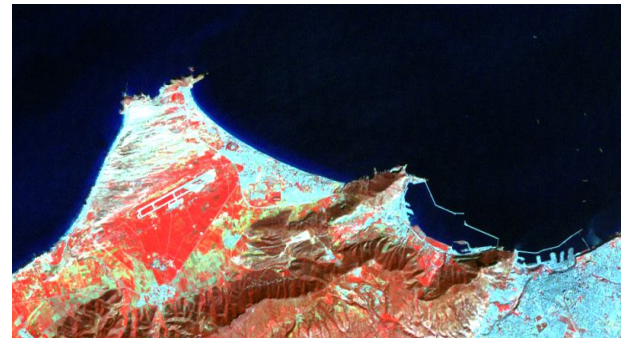
(b)

Figure 4: Images used, (a) synthetic image, (b) satellite image (themes are confusing)

For the satellite image, we started our application by loading the three images corresponding to the three channels.

At the end, a contrast enhancement was performed and then a colored composition by combining the blue filter with channel TM1, the green filter with channel TM3 and the red filter with channel TM4

The application of the SFLAvar proposed approach, like any population-based evolutionary algorithm, depends on several parameters such as population size (μ), number of communities (m), jump (R), fitness function (f) [17], etc. etc. For this we varied the size of the population, the number of communities and the number of individuals in each community as well as the frog jump and the number of iterations.

5.1. Test 1

The first test is to set the iteration number (it) to 1 and vary the frog jump (R), the number of community m representing the maximum number of classes in the image as well as the size of the population μ which is the product of the number of communities and the number of individuals in each community.

The results obtained indicate the fitness functionas well as the necessary execution time and they are recorded in Tables 1.b and Table 2.b, and the corresponding images are illustrated in Tables 1.a and Table 2.a.

This test was applied to both synthetic and satellite images.

Table 1.a: Result of synthetic image classification by SFLAvar, with IT=1, μ/m= (9/3, 36/6, 48/8), varying R to 0.5, 1 and Rand.
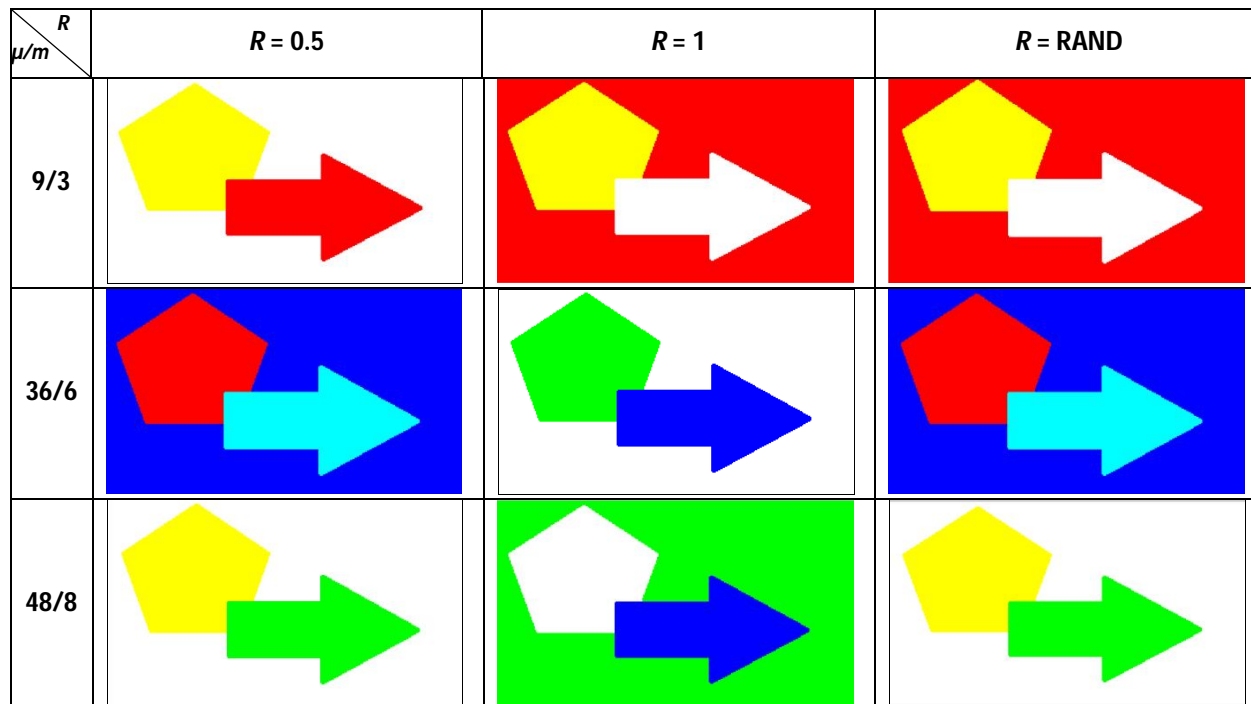
R \ μ/m	R = 0.5	R = 1	R = RAND
9/3			
36/6			
48/8			

Table 1.b: Evaluation of synthetic image classification by SFLAvar, with it=1, μ/m= (9/3, 36/6, 48/8), varying R to 0.5, 1 and Rand.

μ/m		R=0.5	R=1	R=RAND
9/3	Fitness Fonction F	0.8863	0.60410	0.8205
	Execution Time	6.765	7.9837	6.1284
36/6	Fitness Fonction F	1.08	0.93	0.9833
	Execution Time	11.03	11.69	13.35
48/8	Fitness Fonction F	0.9111	0.8884	0.9727
	Execution Time	14.4821	15.5114	13.2384

Table 2.a: Result of satellite image classification by SFLAvar, with IT=1, μ/m = (9/3, 36/6, 48/8), varying R to 0.5, 1 and Rand.
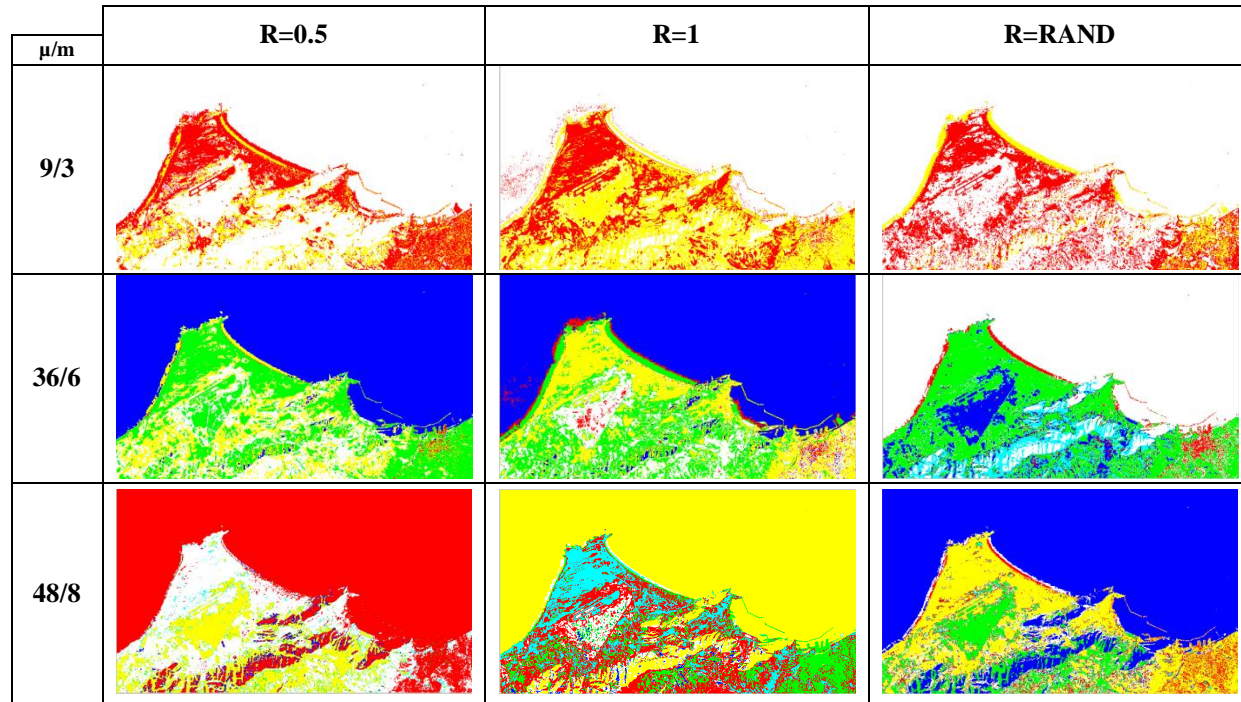

Table 2.b: Evaluation of satellite image classification by SFLAvar, with IT=1, μ/m= (9/3, 36/6, 48/8), varying R to 0.5, 1 and Rand

μ/m		R=0.5	R=1	R=RAND
9/3	Fitness Fonction F	0,953728	0,94317	0,972575
	Execution Time	179,704485	171,3914	171,737521
36/6	Fitness Fonction F	0,8281	0,7228	0,7634
	Execution Time	216.357377	204,015984	204,82575
48/8	Fitness Fonction F	0,73918	0,733328571	0,7738
	Execution Time	208,227674	251,503158	228,339308

5.2. Discussion of Test 1

Based on the results indicated in tables 1 and 2, noting that:

By varying the frog jump (R) to R = 0.5, R= 1 and R = RAND (random value between 0 and 1) and, the best results were found to be satisfactory at R =1 while a random value (RAND) of R can cause divergence.

By varying the population/community size (μ/m), the results obtained show that a small population size generates a small diversity of the population; otherwise (μ high) insignificant regions appear.

Other tests were carried out (u/m = 36/3, 48/5, 48/6, 48/4) to evaluate this approach, which led us to conclude that there must be a balance between the number of individuals in each community.

It should be noted that the best results in terms of quality, execution time and objective function were achieved with R =1, μ = 36 et m = 6 for both images.

In the next tests R will be set to 1.

5.3. Test 2

In this test we will use the same population/community parameters (u/m = 9/3, 36/6, 48/8) and we will vary the number of generations (iterations) IT to 1; 2; 3; 6; 10 and 50 (with R =1).

The results obtained are shown in Table 3.b and the corresponding images are shown in Table 3.a.

Table 3.a: Result of satellite image classification by sflavar, with R =1, μ/m = (9/3, 36/6, 48/8), varying IT to 1.2.3.6.10.

Table 3.b: Assessment of satellite image classification by SFLAvar, with R =1, μ/m= (9/3, 36/6, 48/8), varying IT to 1.2.3.6.10.

| IT \ μ/m		9 /3	36 /6	48 /8
It=1	Fitness Fonction F	0,94317	0,7228	0,733328571
	Execution Time	171,3914	204,015984	251,503158
It=2	Fitness Fonction F	0.9442	0,668425	0,698966667
	Execution Time	194,4713	222,023749	258,228484
It=3	Fitness Fonction F	0.92031	0,659975	0,66363
	Execution Time	201.54	239,012941	278,10997
It=6	Fitness Fonction F	0.91987	0,622475	0,6315875
	Execution Time	219.601377	289,852953	321,724128
It=10	Fitness Fonction F	0.9241	0,62601	0,633757143
	Execution Time	243.21354	355,0377	402,551748
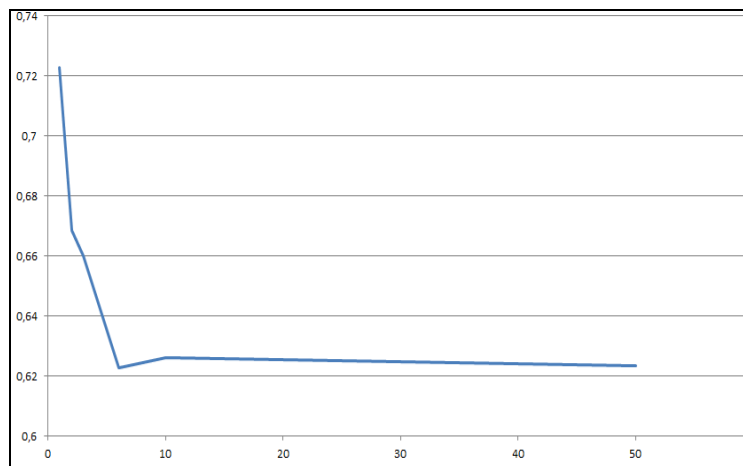
Figure 5: The evolution of the fitness function of the satellite image according to the number of iterations IT=50.

5.4. Discussion of Test 2

From the results obtained, shown in tables 3.a and 3.b, we can notice that the quality of the unsupervised classification of the image is satisfactory, the classes constituting the image have been well detected, however there is some confusion between classes, this is mainly due to the near radiometric value.

Figure 5. contains a graph showing the evolution of the fitness function of the satellite image during 50 iterations. From this graph, we note that our approach begins to converge from the third iteration and stabilizes from the 10th iteration.

By increasing the μ/m combination to 48/8 the algorithm was able to detect exactly the number of classes constituting the image Table 4 indicates the number of pixels in each class.

Table 4. Number of affected pixels in each class making up the satellite image with R=1, μ/m = 48/8 and IT=10.

Classes constituting the satellite image	Number of pixels
Class 1	15658
Class 2	190343
Class 3	51157
Class 4	29100
Class 5	2281
Class 6	31461
Class 7	0
Class 8	0

6. CONCLUSION

In this paper we developed a new SFLAvar approach for the unsupervised classification of satellite images based on the Shuffled Frog-Leaping Algorithm (SFLA) method and the operators of evolutionary algorithms variations.

The performance of the proposed approach depends on the appropriate selection of parameters (POPULATION SIZE, NUMBER OF COMMUNITIES, JUMP,). Notwithstanding the confusions observed, the results obtained were conclusive in terms of quality of classification and time of execution and objective function. Therefore it is suggested to integrate data other than the radiometric value such as texture, ground truths and multi-sensor images.

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