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Alsat-2B/Sentinel-2 Imagery Classification Using the Hybrid Pigeon Inspired Optimization Algorithm

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Abstract

Classification is a substantial operation in data mining, and each element is distributed taking into account its feature values in the corresponding class. Metaheuristics have been widely used in attempts to solve satellite image classification problems. This article proposes a hybrid approach, the flower pigeons-inspired optimization algorithm (FPIO), and the local search method of the flower pollination algorithm is integrated into the pigeon-inspired algorithm. The efficiency and power of the proposed FPIO approach are displayed with a series of images, supported by computational results that demonstrate the cogency of the proposed classification method on satellite imagery. For this work, the Davies-Bouldin Index is used as an objective function. FPIO is applied to different types of images (synthetic, Alsat-2B, and Sentinel-2). Moreover, a comparative experiment between FPIO and the genetic algorithm genetic algorithm is conducted. Experimental results showed that GA outperformed FPIO in matters of time computing. However, FPIO provided better quality results with less confusion. The overall experimental results demonstrate that the proposed approach is an efficient method for satellite imagery classification.

Keywords

Alsat-2B, Davies-Bouldin Index, Flower Pollination Algorithm, Genetic Algorithm, Pigeon-Inspired Optimization, Satellite Image Classification, Sentinel-2

1. Introduction

Due to environmental condition factors, low resolution, and low luminosity, satellite images need processing, such as segmentation or classification. Thus, obtaining an efficient algorithm for the treatment of an image is a crucial task. In the 1950s and 1960s, a computer scientist, John Holland, modeled the concept of evolution, which was introduced into the genetic algorithm (GA) [1]. The basic GA is characterized by fitness evaluation, selection, crossover and mutation of a new population [2]. In this context, more biologically inspired algorithms were conceived to overcome the limits of the algorithm: the descent of the gradient in the resolution of optimization problems. These include the flower pollination algorithm (FPA) [3], bat algorithm [4], artificial bee colony (ABC) [5], particle swarm optimization (PSO) [6], and bacterial foraging optimization algorithm (BFOA), which were adapted and utilized in imagery classification [7].

Optimization can be explained as a process of finding the position of the best solution for a given

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problem; the research process can be performed using agents based on mathematical calculations, but it is not always guaranteed that the best solution can be exploited. For this, we propose combining the pigeon-inspired optimization algorithm (PIO), which was first proposed by Duan and Qiao [8] with the FPA [3] for the classification of satellite images, using the Davies-Bouldin Index (DBI) as an objective function [9]. The flower pigeons-inspired optimization algorithm (FPIO) image classification algorithm will be tested on several types of images (synthetic and satellite). The results obtained will be compared with those obtained by GAs.

In what follows, we present the data used for our demonstration in Section 3. Section 4 gives a brief explanation of FPA and PIO followed by the basic mathematical model of PIO and FPA hybridization. Subsequently, the results of tests and comparisons are contained in Section 5. The conclusion of this article is discussed in Section 6.

2. Related Work

In 2012, Yang [3] proposed a FPA inspired by the proliferation process of flowers and explained how the new algorithm contributed to solving a nonlinear design benchmark. Adding the possible extensions that can be explored by researchers to solve combinatorial optimization problems.

In 2014, Duan and Qiao [8] presented a novel swarm intelligence optimizer, namely, the pigeon-inspired algorithm. In this newly presented algorithm, information sharing between the individuals constituting the population is highlighted. The principal objective of the algorithm was to mimic pigeons' homing behavior using magnetic fields and landmarks as inputs. This approach was applied to solve air robot path planning problems.

In 2017, Li et al. [10] shared their work on an improved version of the PIO (IPIO) algorithm aiming to solve clustering problems. The flying directions were navigated using a parametric control strategy, and the combination of the climber process Monkey algorithm with dimension-by-dimension improvement was applied to enhance the local search. Experimental results over six real datasets were presented. As a result, IPIO is an optional method for solving the clustering analysis problem.

In 2019, Abdel-Basset and Shawsky [11] approached issues related to the FPA in a comprehensive review, and a comparison of the FPA with six distinct metaheuristics, including the grasshopper optimization algorithm, was made to solve a constrained engineering optimization problem. The results analyzed statistically with a nonparametric Friedman test indicate the effectiveness and superiority of FPA in solving the given problem.

In 2019, Hu et al. [12] applied the adaptive operator quantum-behaved PIO (QPIO) algorithm to unmanned aerial vehicle (UAV) path planning. Due to the low global convergence speed and local optimum of the QPIO, a new initialization process was introduced, as well as the gradual decreasing pigeon population-updating strategy to prevent premature convergence and local optima. The approach was compared with the PSO to solve UAV with the results indicating the better execution of the proposed algorithm regarding accuracy and convergence.

In 2019, Cui et al. [13] triggered by the limitation of the original PIO and multi-objective pigeon-inspired optimization (MPIO) in solving many-objective optimization problems (MaOPs), the authors proposed MaPIO summed up in adopting balanceable fitness estimation (BFE) mechanism, to overcome

Pareto ranking and decomposition in maps. Moreover, the modification of the MPIO velocity update equation acquires the ability to provide additional search direction and consequently solve maps.

In 2019, Liu et al. [14] presented an extended version of an end-to-end framework leveraging an improved architecture of the deep sat framework based on two deep belief networks (DBNs). The new version augments a convolutional neural network (CNN) with handcrafted features. This framework was applied on the Sat-4 and Sat-6 datasets, achieving 99.9% accuracy for handcrafted features and 99.84% accuracy for CNN feature maps.

In 2020, Alweshah et al. [15], with the aim of increasing the classification accuracy, suggested the hybridization of probabilistic neural network (PNN) with the FPA, where the FPA has been directed into defining the optimal parameter value for the neural network weights. The results demonstrated that the hybrid model was more effective than the original model.

In 2020, Rai et al. [16] applied the Brovey transform method to merge panchromatic bands with three RGB bands and then reduced the dimensions of the image using principal component analysis. The classification was made by means of the CNN.

In 2020, FPGA-based hybridization was introduced for satellite image classification [17]. They chose the spiking dense layer for classification and the classical non-spiking CNN for feature extraction. The results demonstrated the reduction of hardware resource intensiveness for the classification stage and an equivalent recognition performance to the classical counterpart.

In 2020, Tuba et al. [18] proposed a bare bone fireworks algorithm for K-means optimization. A standard benchmark dataset was tested, and the results were compared to the basic K-means algorithm, demonstrating that the proposed approach gave a better performance in regards to image classification.

3. Materials

3.1 Study Area

For this work, the different types of images were used as shown in Fig. 1.

Alsat-2. The region chosen is situated in Algiers (E03°04'12" N36°47'37" 1051 1053). For the demonstration case, we created three regions of interest from this image.

Sentinel-2. The region chosen is located between Oran and Mostaganem in northwest Algeria (N35°47'00", W0°10'00"), and it is characterized by a steppe climate where the annual average temperature of 18.3°C, the area is at an average altitude of 12 m, with the mean precipitation reaching 376 mm per year.

Synthetic image. A synthetic image was created with the purpose of testing our proposed approach's performance, and the image contains four classes.

Alsat-2. The image used for our test represents the dam of Sidi Abdelli (Tlemcen) (N35°04'00", W1°08'00").

3.2 Data

In this paper, we use a synthetic image (Fig. 1(c)) with Alsat-2 imagery level-2A product (Algiers, Tlemcen) from September 26, 2016 and October 3, 2018 (Fig. 1(a) and 1(d)). Sentinel-2 imagery level-2A product bottom of atmosphere (Oran) from December 16, 2019 for better explanation (Fig. 1(b)). Due to their atmospheric applications, the 60 m spectral bands have not been exploited [19]. Considering the visible spectral bands of Sentinel-2 imagery, a resampling process was performed using the closest neighbor method with three spectral bands (B2, B3, B4) from a 10-m spatial resolution within the SNAP 7.0 toolbox (European Space Agency, Paris, France).

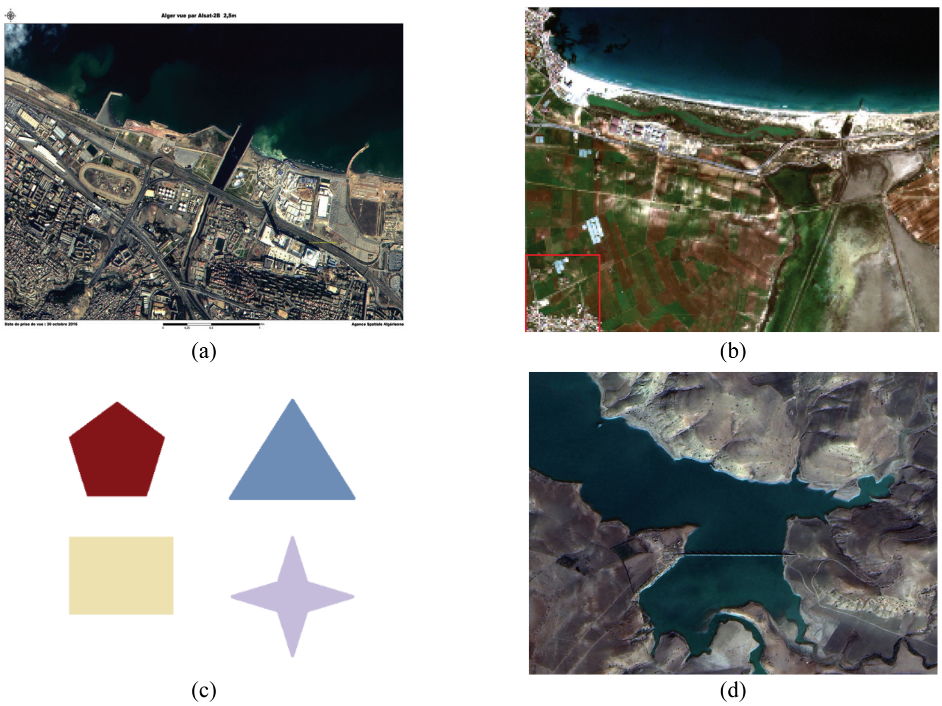

Fig. 1. (a) Alsat-2 imagery of the region in Algiers. (b) Sentinel-2 imagery of the region is located between Oran and Mostaganem. (c) Synthetic image created with the purpose of testing. (d) Alsat-2 imagery used for our test represents the dam of Sidi Abdelli (Tlemcen).

4. Method

4.1 Bases of Pigeon-Inspired Optimization

Homing pigeon behavior largely influenced PIO [8] as a bioinspired optimization tool and was the main inspiration for the approach cited by the authors of the article; two operators were designed by using some rules.

Until recently, researchers focused on animal sailing mechanisms at the degree of the individual [20]. However, with the evolution of the studied problem complexity, researchers turned their interest to group behavior similar to migratory species [21], noting the ability of social interactions to alter the decision of migratory movement [22,23].

During their movement, an animal group relies on a variety of sensors, such as celestial bodies, landmarks, light polarization, magnetic fields, and odors [24].

Using landmarks, magnetic flux, and the sun, homing pigeons are able to find their way home. Directions are regulated with their compasses; the magneto receptors sense the earth field employed in shaping the map in their brains. As they get closer to the destination, they rely on cues to locate themselves and slowly become independent of the magnetic field. Pigeons without knowledge of the cues will follow other pigeons that are aware of the cues and fly directly to the destination.

The magnetic flux and therefore the sun are taken into consideration for the presentation of the compass and map operator model, and the model of the landmark operator relies on landmarks [25].

A mathematical model has been developed by Guilford et al. [26]. This model can predict at what time the technique utilized by the pigeons will vary.

4.1.1 Mathematical model of PIO

To mimic homing pigeon characteristics, the following rules are used to design two operators.

Compass and map operator: Pigeons use magnetoreception to create the map in their brains. To adjust the direction, they consider the altitude of the sun as a compass.

The conditions during this operator are defined with the velocity W_i and the position Z_i of pigeon *i*. In each iteration, the positions and velocities are updated in a D-dimensional search space. At the *t*-th iteration, we calculate the new velocity W_i and the new position Z_i of pigeon *i* with Eq. (1) and Eq. (2), respectively, as follows:

$$W_i(t) = W_i(t-1) \cdot e^{-Rt} + rand \cdot \left(Z_g - Z_i(t-1)\right) \tag{1}$$

$$Z_i(t) = Z_i(t-1) + W_i(t) \tag{2}$$

The compass and map factors are represented by R. By comparing all the pigeon's positions, we can obtain the current best global position, which is defined by Z_g.

The use of the compass and map guarantees the best positions of all pigeons. When following this exact pigeon, each pigeon would be able to adjust its flying direction pigeon according to Eq. (1).

Landmark operator: the pigeons depend upon neighboring landmarks when flying near their destination if they are unacquainted with the landmarks, they are going to track the conversant in the landmarks pigeons else they will fly straight to the destination. The total number of pigeons is decreased by half with N_p in every generation. However, the pigeons are still distant from the destination, and they are unacquainted with the landmarks. At the *t*-th iteration, $Z_c(t)$ represents the kernel of some pigeon's position, with the ability of every pigeon to fly straight to the destination as a hypothesis. The position updating rule for pigeon *i* at the *t*-th iteration is given by:

$$H_p(t) = \frac{H_p(t-1)}{2} \tag{3}$$

$$Z_c(t) = \frac{\sum Z_i(t) \cdot fitness\,(Z_i(t))}{H_p \sum fitness(Z_i(t))} \tag{4}$$

$$Z_i(t) = Z_i(t-1) + rand \cdot \left(Z_c(t) - Z_i(t-1)\right) \tag{5}$$

The quality of the individual pigeon is defined by a fitness function. For minimization, the following fitness formula can be used: $\left(Z_i(t)\right) = \frac{1}{f_{min}(Z_i(t))+\varepsilon}$.

For maximization and optimization problems, we can choose the fitness $\left(Z_i(t)\right) = f_{max}\left(Z_i(t)\right)$. For each pigeon, the best position of the Hc^{th} iteration can be labeled with Z_p , and $Z_p = \min(Z_{i1}, Z_{i2}, \dots, Z_{iNc})$.

4.2 Bases of the Flower Pollination Algorithm

The FPA [3] is a meta-heuristic inspired by Nature. The process of flower reproduction relies mainly on pollination, which is accomplished by pollinators that transfer pollen [27] to the same flower or flowers of the same plant; in this case, it is called self-pollination. For the second type of pollination, cross-pollination, pollen is transferred from one plant to another with the help of abiotic or biotic agents [28]. Bats, birds, and insects are the principal pollinators in this operation. For this research, the FPA is mentioned and partially used to contribute to classification data problem solving [11].

The following rules summarize the above characteristics of the pollination process, flower constancy, and pollinator comportment:

– Cross-pollination and biotics are considered a global pollination process with pollen-carrying pollinators performing fewer flights;
– Local pollination is the combination of both abiotic and self-pollination;
– The probability of reproduction is proportional to the similarity of two flowers and represents flower constancy;
– The switch probability $q \in [0, 1]$ is what controls global and local pollination.

4.3 Davies-Bouldin Index

The DBI is an indexation method usually used in satellite image classification [29,30] to evaluate the performance of the solution, and it is based on the cluster similarity measure R_{kj}, which is based on the dispersion measurement S_k and the dissimilarity measurement D_{kj} of a cluster. Generally, R_{kj} is defined as follows:

$$d_{kj} = d\left(v_k, v_j\right), \quad 1 \leq k, j \leq k; j \neq k \tag{6}$$

$$S_k = \left(\frac{1}{M_k} \sum x_i \epsilon X_k \|x_i - v_k\|^2\right)^{½}, 1 \leq k \leq K \tag{7}$$

$$v_k = \frac{\sum_{i=1}^{N}(\mu_{i,k}) x_i}{\sum_{i=1}^{N}(\mu_{i,k})} = \frac{\sum_{x_i \epsilon X_k} x_i}{M_k}, 1 \leq k \leq K \tag{8}$$

$$\mu_{kn} = \begin{cases} 1; & \|x_n - u_k\| \leq \left\|x_n - u_j\right\| \\ 0; & otherwise \end{cases}, \quad 1 \leq k, j \leq K, j \neq k; 1 \leq n \leq N \tag{9}$$

where

x_n: Object n.

N: Total number of pixels.

u_k: Individual i of the previous iteration (generation).

v_k: Average calculated for each class k.

K: Maximum number of classes.
μ_{kn}: Belonging function of each x_n pixel belonging to the i class.

$$R_{kj} = \frac{S_k+S_j}{d_{kj}} \quad (10)$$

The DBI is defined as

$$DB = \frac{1}{k}\sum_{k=1}^{I} R_k \quad (11)$$

where

$$R_k = \max_{j=1\ldots nc, k\neq j}\left(R_{kj}\right), \ \ k = 1 \ldots K \quad (12)$$

The goal of functional classification is to minimize DBI [30]. Consequently, $\frac{1}{DB_j}$ is the definition of the chromosome j fitness function.

4.4 FPIO Application for Unsupervised Classification

In the following paragraphs, unsupervised classification of Sentinel-2, Alsat-2, and synthetic images using FPIO are explained. In particular, every PIO operation (such as the map and compass operator or Landmark operator) is described. Satellite images are composed of several bands depending on the type of satellite acquiring them. A high number of bands involve a more significant quantity of data that contains a large amount of irrelevant and redundant information [31]. In this case, we are conducting our tests on satellite images with different characteristics, such as the number of bands and size.

Although the basic PIO has been widely used for solving complex optimization problems and has proven to be superior in some practices, there are still some shortcomings, such as prematurity of convergence and lack of diversity [32]. In this research, a FPA function has been integrated to enhance the standard PIO performance; therefore, it addresses the prementioned problems. The FPIO strategy is based on the position, compass and landmark operators where the PIO algorithm has been modified to optimize the research procedure. After the step of updating the velocity and position of the pigeons, a condition was introduced to choose between the global using PIO operators or local search using the FPA operator present in the FPA (Fig. 2).

First, the fitness of the initial population is evaluated, and the choice of the best path is conducted using the DBI as an objective function. After that, the hybrid pigeon-inspired optimization algorithm implementation procedure is followed according to the following steps:

Hc_{1max}: The maximum number of generations that the map and compass operation is carried out.
Hc_{2max}: The maximum number of generations that the landmark operation is carried out.
Hc: Number of generations.

Step 1: Load the data to be processed.
Step 2: Introduce the value of each parameter, such as the hunting zone, setting of the magnetic field, global search algebra, local search algebra, and switching probability value (Table 1).
Step 3: Randomly assign a velocity and a path to each pigeon and evaluate the fitness of each pigeon to locate the best current path.

Step 4: Update the path and velocity of every pigeon with Eqs. (1) and (2) using a compass and map operator. Continue with the comparison of all the pigeon's fitness to find the new best path.

Step 5: If *rand* < q, local search occurs using the FPA method if this step is omitted, and the global search will be carried out instead.

Step 6: Hold the compass and map operator and start the next operator if $Hc > Hc_{1max}$. If it is omitted, go to Step 4.

Step 7: After relying on the fitness values to classify the pigeons, the pigeons with the highest fitness values will be followed by half of the pigeons with the lowest values according to Formula (3), then the center of all pigeons that is the desirable center will be found, according to Formula (4), all the pigeons will adjust their flying direction according to Formula (5) to get to the destination. We save the best solution.

Step 8: If $Hc > Hc_{2max}$, hold the landmark operator, and reveal the results. If it is not, go to Step 7.

Algorithm 1. Pseudo-code FPIO

FPIO algorithm Input
H_p*: number of individuals in pigeon swarm.*
D: dimension of the search space.
R: map and compass factor.
Search range: borders of the search space.
Hc_{1max}*: maximum number of generations that the map and compass operation is carried out.*
Hc_{2max}*: maximum number of generations that the landmark operation is carried out.*
Output
Z_g*: global optima of the fitness function f.*
q: probability.
Epsilon ∈ *[o,1]*

1. Initialization
Set initial values for Hc_{1max}, Hc_{2max}, H_p, *D, R and the search range*
Set initial path Z_i *and velocity Wi for each pigeon individual*
Set Z_p=Z_i, H_c *=1*
Calculate fitness (DBI) values of different pigeon individuals
Z_g*: =arg min [f(Xp)]*
If *rand < q*

2. Map and compass operations
For H_c*=1 to* Hc_{1max} *do*
for i =1 to H_p *do*
while Z_i *is beyond the search range do*
calculate Wi and Z_i *according to Equations (1) and (2)*
end while
end for
evaluate Z_i*, and update* Z_p *and* Z_g
end for

3. Landmark operations
For H_c *=* Hc_{1max} *+ 1 to* Hc_{2max} *do*
while Z_p *is beyond the search range do*
rank all the available pigeon individuals according to their fitness values
H_p *=* H_p*/2*
keep half of the individuals with a better fitness value and abandon the other half

Z_c = average value of the paths of the remaining pigeon individuals
calculate Z_i according to Equation (5)
end while
evaluate Z_i, and update Z_p and Z_g
end for
Else
4. Local search using FPA
For H_c = 1 H_p to do
Draw ε from a uniform distribution in [0,1]
Randomly choose j and k among all the solutions
Do local pollination via

$$Z_i^{t+1} = Z_i^t + \varepsilon(Z_j^t - Z_k^t)$$

End if
Output
Z_g is output as the global optima of the fitness function f

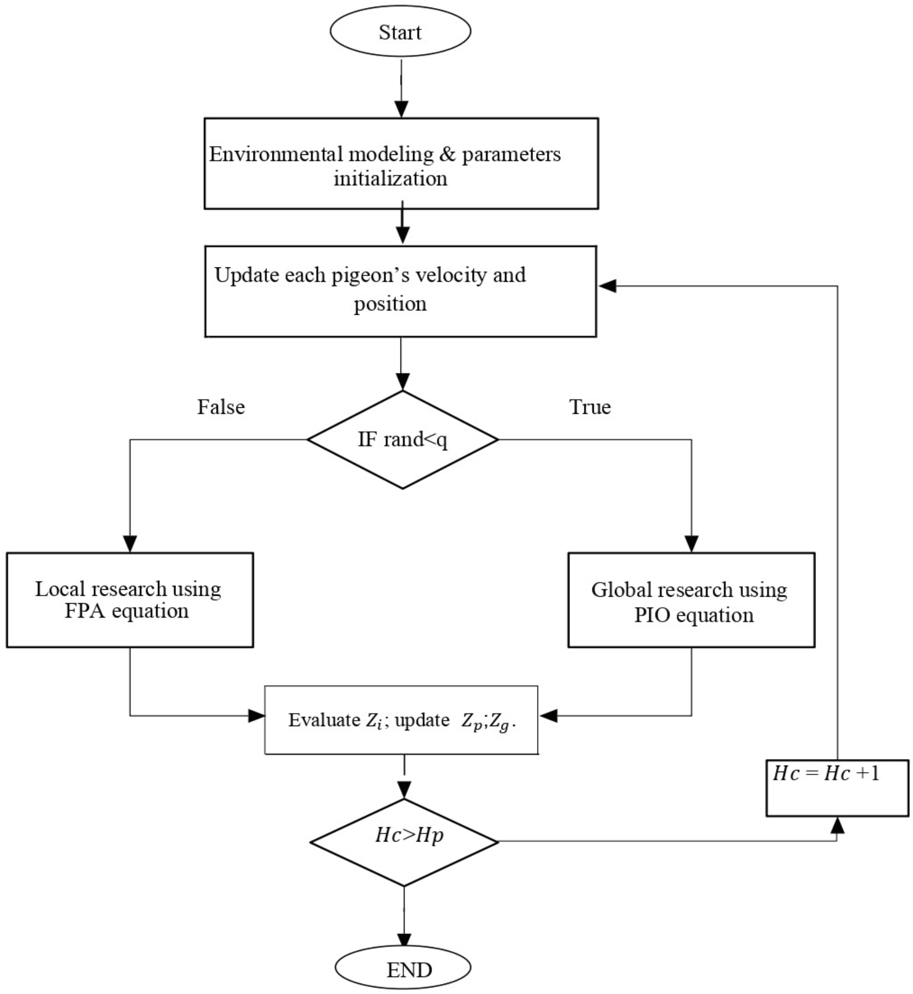

Fig. 2. Flowchart of the flower pigeon-inspired optimization algorithm (FPIO).

Table 1. Initial parameters of FPIO

Parameter	Description	Value
Pigeonnum	Number of pigeons	30
T1, T2	Global, local search algebra	90, 15
D	Dimensionality	2
R	Parameters of the magnetic field	0.3
Bound	Hunting zone	[30,30]
Q	Switching probability	0.8
ε	Epsilon	[0,1]

5. Experimental Results

5.1 FPIO Performance on Different Type of Images

The FPIO classification process was performed on different types of images. In the proposed work, a hybrid pigeon by FPA was used to classify satellite images. Since it does not have the inbuilt property of clustering, the hybridization of the PIO and FPA was used to find the clusters of similar land cover and was made to optimize the research process.

To evaluate the FPIO method, an experimental study was conducted on Alsat-2 and Sentinel-2 imagery. In this context, we compared it to the GA results [30,33] for the classification of satellite imagery.

For the preliminary evaluation of the proposed approach, the parameters were fixed for two Alsat-2B, Sentinel-2 and synthetic images (Fig. 3). We demonstrate the effectiveness of FPIO, which is supported by the classification rate, and the best DBI values in Table 2, which have proven to be satisfactory.

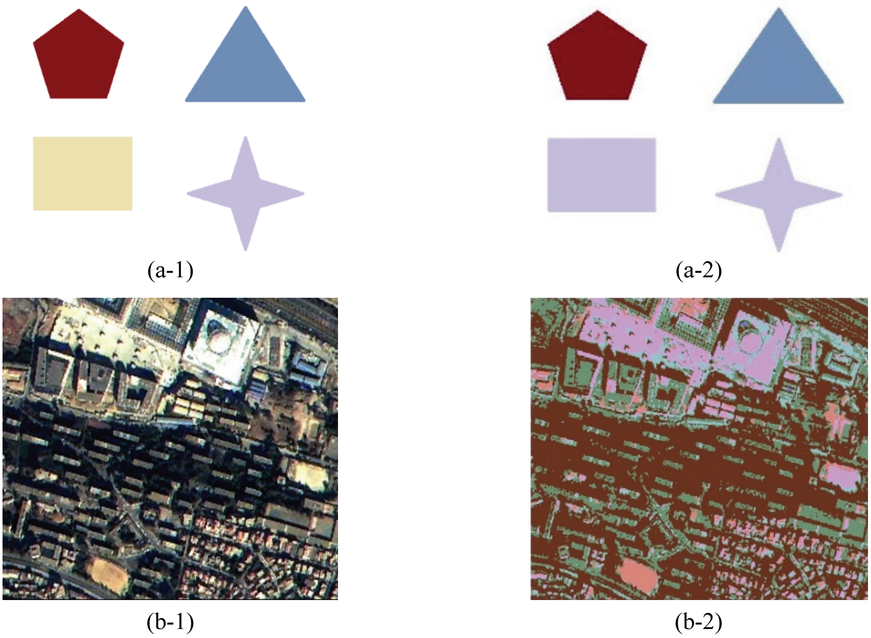

Fig. 3. Images (a-2), (b-2), (c-2), (d-2), (e-2), and (f-2) representing unsupervised classification of (a-1), (b-1), (c-1), (d-1), (e-1), and (f-1) with FPIO.

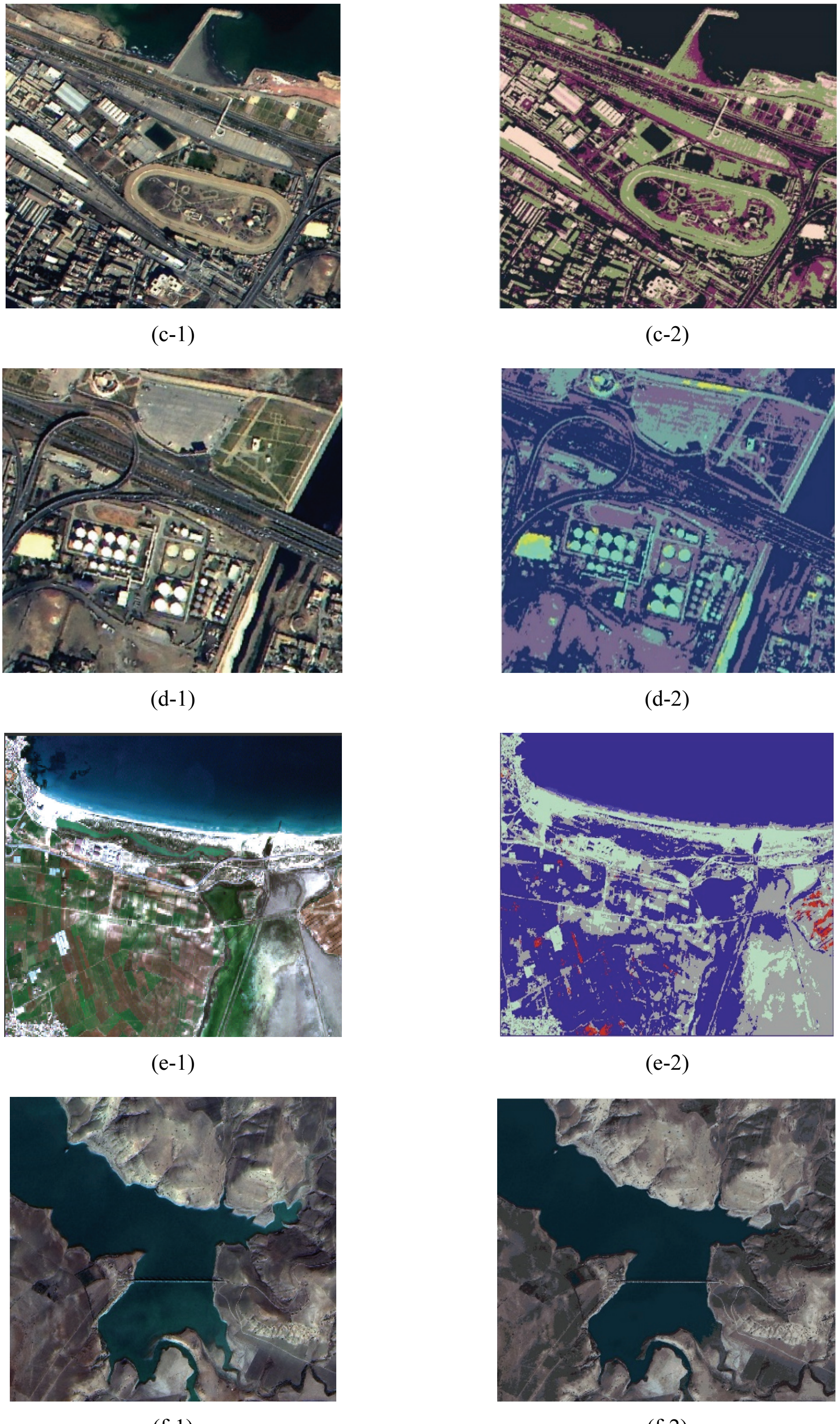

Fig. 3. Continued.

Table 2. Evaluation of the classification results on various images

	Population number (Pop)	Best DBI	Execution time (s)	Classification rate (%)
Fig. 3(a-2)	30	0.2498	9.762868	88.60
Fig. 3(b-2)	30	0.6607	213.177856	82.87
Fig. 3(c-2)	30	0.8365	87.004404	81.70
Fig. 3(d-2)	30	0.7084	83.449694	84.90
Fig. 3(e-2)	30	0.7388	39.243018	82.00
Fig. 3(f-2)	30	0.3354	446.366711	83.40

5.2 Influence of the Population Size

In this part, the results of the following experiment are revealed. In this context, the behavior of the FPIO-based DBI is evaluated by checking the presence of each class of the initial image in the resulting classification. The results acquired showed that varying the size of the population affects the outcome, increasing the size of the population makes us end up with better results in terms of solution quality (minimal DBI), but it affects the execution time of our algorithm that increases.

From the results of Fig. 4, the classification was well operated with the proposed approach for different values of the population number (Pop). Based on Table 3, the number of populations influences the quality of the results, where it is clearly perceived that a smaller population gives a better classification rate, which is translated visually to the naked eye.

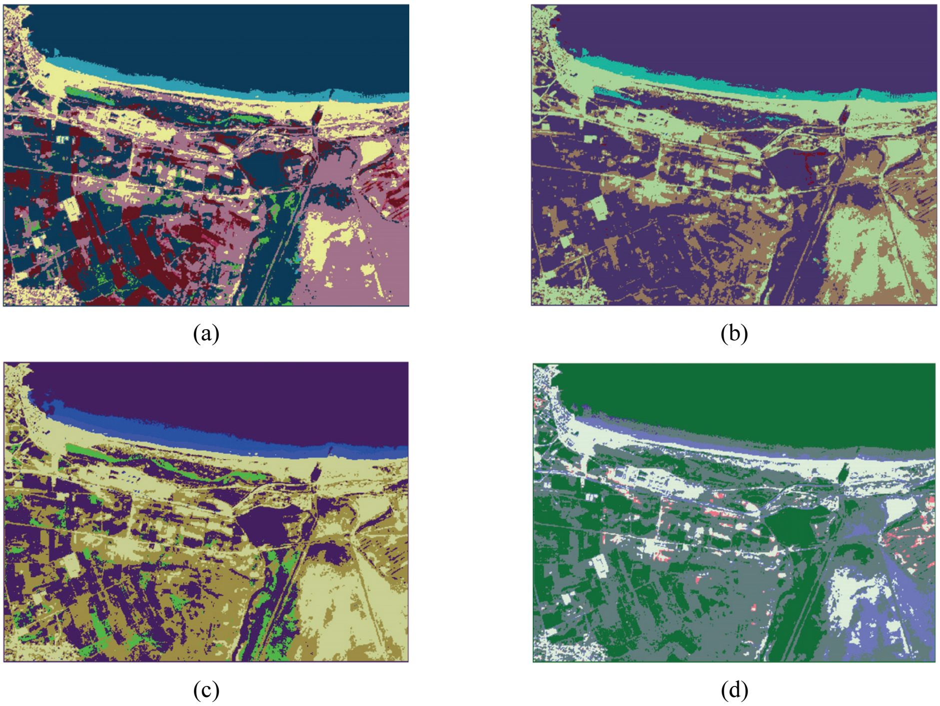

Fig. 4. Results of the classification of Sentinel-2 images with the different value of population number: (a) Pop4=10, (b) Pop4=20, (c) Pop4=30, and (d) Pop4=40.

Table 3. Assessment of the classification of the Sentinel-2 image by changing the size of the population

	Pop4	Best DBI	Execution time (s)	Classification rate (%)
Sentinel-2 image	10	0.5335	17.670299	82.36
	20	0.7468	25.485085	81.38
	30	0.8572	35.112484	81.94
	40	0.7288	52.362682	82.73

5.3 FPIO and GA Performance Comparison

To estimate the performance of our proposed FPIO method with the GA performances, we took the two algorithms previously mentioned and applied them to the same satellite images and a synthetic image using the same parameters for the two algorithms, and we proceeded by choosing the best result obtained by each algorithm.

The results illustrated in Fig. 5 of the comparison demonstrate that the quality of the results obtained by the FPIO classification is greater than the GA [2] classification considering the quality of the solution (minimal DBI) and execution time, as demonstrated in Table 4. FPIO takes more time than GA alone to provide the results.

This paper focuses on introducing a promising approach for image classification. Hence, FPIO was compared to a fairly used meta-heuristic, namely, the genetic algorithm. The same images were computed with both algorithms; the results given in Table 4 state that GA is faster with computational time depending mostly on the image size. However, the DBI measurements given by FPIO are much better, which provides better quality results with less confusion in the outputs (Fig. 5).

Table 4. Comparison of the FPIO classification results with GA classification

		Pop4	Best DBI	Execution time (s)	Classification rate (%)
GA	Alsat-2	30	0.8710	134.896372	81.79
	Sentinel-2	30	0.7708	22.796095	83.87
	Synthetic	30	0.7700	385.907010	75.70
FPIO	Alsat-2	30	0.5228	221.050000	82.12
	Sentinel-2	30	0.3019	43.356234	81.87
	Synthetic	30	0.1544	63.259459	87.95

(a-1) (a-2) (a-3)

Fig. 5. Satellite images (a-1), (a-2), and synthetic image (a-3). Genetic algorithm classification results (b-1), (b-2), (b-3) and FPIO classification results (c-1), (c-2), (c-3). The David-Bouldin Index was used with both algorithms.

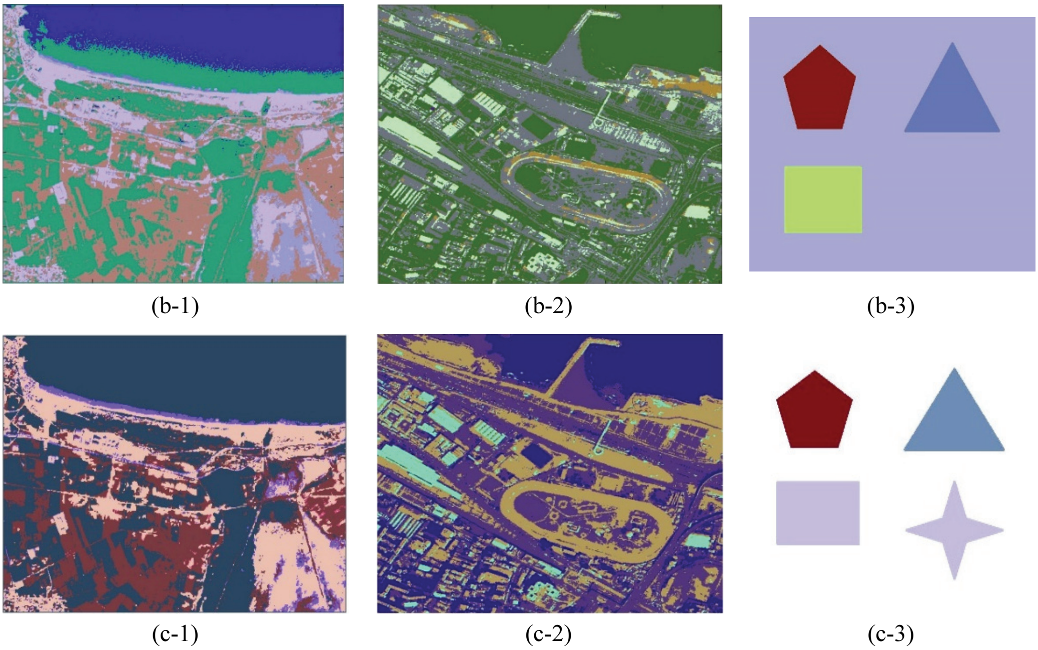

Fig. 5. Continued.

6. Conclusion

Herein, we proposed the FPIO algorithm to solve classification problems. The FPIO approach is founded on the hybridization of PIO with the FPA in favor of image classification. The local research operator of the FPA was employed to improve the classification rate. The potential of the approach has been estimated with a variety of experiments. Certain biological aspects of FPA and PIO have been combined to create a powerful tool that can eliminate some shortcomings of the original algorithms. Since FPA initially has both local and global research functions, it consumes a significant amount of time with a less efficient convergence rate. On the other hand, FPIO manifested its efficiency in the case of indexing for image classification using the DBI. A comparison study between AG and FPIO for satellite image classification was also conducted. In terms of classification quality, FPIO outperformed the GA. Therefore, in the case of fast convergence, the FPIO is advantageous to avoid premature convergence and not become trapped within local optima. Furthermore, it is possible to better exploit this proposed algorithm by conducting a study of parameters taking into consideration the nature of the problem to solve. The experimental results indicated that the FPIO algorithm has great promise in solving satellite image classification.

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