Acta Scientific COMPUTER SCIENCES

Volume 2 Issue 12 December 2020

Research Article

Application of the Pigeon Method to the Classification of Captured Data

Yasmine Benyettou* and Hadria Fizazi

University of Sciences and Technology of Oran, USTO, Algeria

***Corresponding Author:** Yasmine Benyettou, University of Sciences and Technology of Oran, USTO, Algeria.

Received: September 24, 2020

Published: November 18, 2020

© All rights are reserved by **Yasmine Benyettou and Hadria Fizazi.**

Abstract

This paper presents a method to increase the classification performance of satellite images by swarm intelligence. Traditional statistical classifiers have limitations in solving complex classification problems due to their harsh assumptions because these methods only examine spectral variance by ignoring the spatial distribution of pixels corresponding to land cover classes and the correlation between the different bands.

An optimization algorithm inspired by the behavior of pigeons is applied and has been used in various fields such as image restoration, planning of the trajectories of aerial robots. In our case, the basic idea is: Davies-Bouldin (DBI) is used as a fitness function. The iterative optimization process is carried out by the pigeon optimization algorithm. In this process, the fitness function matches the coordinate of the pigeon in optimizing the problem. The best result is obtained when the pigeon finds the best overall position. This method converts the problem of finding the optimal solution to the problem of solving multidimensional variables and efficiently optimizes the result.

In order to verify the feasibility and accuracy of the supervised classification, the K-means bisecting technique and the deep learning method were implemented. The results of the comparison indicate that the method based on the inspired pigeon optimization is effective with a good classification rate equal to 95.60%, an accuracy rate of 84.70% in a reduced execution time of 19.15 dry. The results of the calculation also show that the proposed PIO algorithm can effectively improve the speed of convergence, and the superiority of the overall search.

Keywords: Pigeon Inspired Optimization (PIO) Algorithm; K-Means Bisecting; Deep Learning; Satellite Image; Classification

Introduction

Automatic image processing consists of capturing an image, extracting interesting information and finally interpreting that information. Image classification is a classic problem in the processing of image analysis, and it is also one of the difficulties in this field [1].

Classification consists of grouping pixels according to their spectral resemblance or determining the outlines of a group of pixels to form spatial units that can be interpreted in terms of thematic classes or categories.

The problem is therefore to produce spectral classes capable of being interpreted in thematic classes. A very important point concerns the strategy to be adopted for grouping the pixels or groups of pixels so as to form relatively homogeneous spectral classes. The objective is therefore to reduce the information to an optimal level during the generalization process. Spectral classification only makes sense if it is possible to derive a thematic interpretation in terms of land use categories. The correspondence between spectral class and thematic class is often not unequivocal [2].

Due to its high efficiency and ease of use, supervised classification is one of the most widely used techniques in image classification. The advantage is that the speed of calculation makes it possible to work over large areas, The processing operations are objective in the sense that the chosen algorithm acts on the entire image in an identical manner and The results are immediately quantifiable in statistical terms.

Many effective image classification approaches have been reported, such as wide margin separators [3], training discriminating CNNs during deep learning [4], training deep transferable models to use a field classification with high resolution remote sensing images [5]. these algorithms are very simple to implement and quickly converge towards a locally optimal solution.

However, their main drawback is that they have to provide a good quality initial score entry as well as the possible number of classes. These constraints require the use unattractive algorithms when you want to automatically classify an image.

Bio-inspired approaches have also been widely used, they have undergone a particular evolution in recent years thanks to technological advances in machine computing. For example: Gray Wolf Optimization [6] which is a swarm intelligence-based algorithm that mimics the leadership and hunting hierarchy of the gray wolf in the wild and mathematically models. Ant colony optimization for hyperspectral image classification [7] designed to solve graphics-based problems and then extended to other applications such as image classification.

In this article, an inspired optimization algorithm based on the behavior of pigeons is applied that has been used in different fields such as image restoration [8], flight path planning of air robots [9] and segmentation of 'images [10]. In our case, the basic idea is to use the supervised classification method to design the objective function. For this, the Davies-Bouldin function (DBI) is used as a fitness function to be minimized. The iterative optimization process is achieved by pigeon-inspired optimization. In this process, the fitness function matches the coordinate of the pigeon in the pigeon-inspired optimization. The best result is obtained when the pigeon finds the best overall position. This method converts the problem of finding the optimal solution into a problem of solving multidimensional variables and efficiently optimizes the result.

The objective of this article is to see the feasibility, performance, and accuracy of improving supervised classification with the PIO algorithm on SAT images and reducing runtime as well as error rate while by having a good classification rate.

The Pigeon Inspired Optimization Algorithm (PIO) consists of two operators, a map and compass operator and a cue operator. To assess the performance of the latter, the K-means bisecting technique and the deep learning method were used. The results indicate that the PIO algorithm is feasible and improves the supervised classification of satellite data, with reduced execution time and gives a more precise result compared to the compared methods.

This article is organized as follows: The second section describes the behavior of the pigeon-inspired algorithm encountered in relation to the mathematical model, coding and objective function. The third section details the PIO pigeon algorithm. Section four explains the coding and objective function in the pigeon model. The experimental results and the simulation are illustrated in the fifth section. Section six presents the work published in this document.

Pigeons inspired optimization

Inspired by the behavior of the pigeons observed above, a bio-inspired swarm intelligence optimizer is proposed for the supervised classification of a satellite image. Based on research, scientists have indicated that orientation in pigeons is mainly based on two operators appearing using certain rules as follows.

Natural behavior of the pigeon

Pigeons are estimated to fly long distances in search of food. They are equally skillful and swift at flying through a forest as through the open space.

Another interesting ability is that, the pigeons can find their route back to their home with their ability to sense Earth's magnetic field, the sun's altitude and visual clues like landmarks. Leading pigeons in the group communicate with rest of the flock and navigates by maintaining a side-by-side flocking distance [7].

A study of the ability of pigeons to detect different magnetic fields shows that the impressive guiding abilities of pigeons depend almost on tiny magnetic particles in their beaks. Specifically, there are iron crystals in the beak of the pigeons, which can give the birds a nose for the north. Studies have showed that species appear to have a system in which signals from magnetite particles are routed from the nose to the brain through the trigeminal nerve [11]. The proof that the sun also participates in the navigation of the pigeon has been interpreted, in whole or in part, in terms of the pigeon's ability to distinguish the difference in altitude between the sun at the base and at the point of release. Recent research on the behavior of pigeons also shows that the pigeon can follow certain landmarks, such as main roads, railways and rivers, rather than going directly to their destination.

Guilford and his colleagues have developed a mathematical model, which predicts when pigeons move from one operator to another. When the pigeons begin their journey, they can rely more on tools resembling compasses. In the middle of their trip, they can use landmarks when they need to reassess their route and make corrections [12].

Mathematical model of PIO

Inspired by the behavior of pigeons observed above, a bio-inspired swarm intelligence optimizer is proposed for the classification of a satellite image. Based on research, scientists have claimed that orientation in pigeons is mainly based on two operators who are designed using certain rules as follows:

Map and compass operator

The birds would use the Earth's magnetic field (CMT) to orient themselves, which would also allow them to take over when the climatic conditions no longer allow visual orientation. This is called magneto reception.

In the PIO model, the rules are defined by calculating the position Xi and the speed Vi of the pigeon i in a search space of dimension D and these are updated during each iteration using Eq. (1) which represent speeds in a research space and Eq. (2) representing positions in the same space.

$$Vi(t) = Vi(t-1).e^{-Rt} + Rand\ (Xg - Xi(t-1) \quad -----(1)$$

$$Xi(t) = Xi(t-1) + Vi(t) \quad ----(2)$$

Where R is the compass map factor, Rand is a random number and Xg is the best global position calculated by comparing all the positions [9,11].

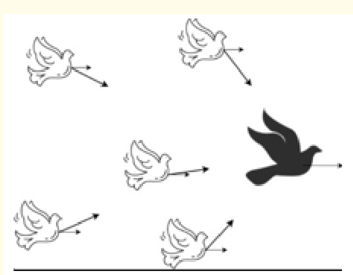

Figure 1: Map operator and compass model.

As shown in figure 1, the map and the compass guarantee the best positions of all pigeons. By comparing all the positions, it is obvious that the position of the pigeon centered on the right is the best. Each pigeon can adjust its direction of flight by following that specific pigeon in accordance with Eq.1, which is expressed by the thick arrows.

The thin arrow represents its former direction of flight, which is linked to VI (t - 1). e $^{-Rt}$ In Eq. (1). The vector sum of these two arrows is its next direction of flight [9].

Landmark operator

When pigeons fly close to their destination, they rely on the landmarks that are nearby. If they know the landmarks well, they will fly directly to the destination. If they are far from the destination and unfamiliar with the landmarks, they will follow the pigeons who know the landmarks well.

Let Xc (t) be the center of the position of some pigeons on the second iteration, and suppose that each pigeon can fly directly to its destination. The position update rule for pigeon i at the tth iteration can be given by [9].

Np (t-1)/2 Where Np is the size of the population.

The new position of other pigeons can be calculated by:

$$X_c(t) = \frac{\sum X_i(t).fitness(X_i(t))}{Np \sum X_i(t).fitness(X_i(t))} \quad ---- (3)$$

And the position of the pigeons $X_i(t)$ is given in Eq.(4) as follow:

$$X_i(t) = X_i(t-1) + rand\big(Xc(t) - X_i(t-1)\big) \quad ---- (4)$$

To calculate the fitness of each individual (Pigeon) in order to solve the minimum optimization problem, it is necessary to calculate the minimum of the Davies-Bouldin index (DBI) [2]:

$$Min\ DBI = \frac{1}{n}\sum_{k=1}^{n} R_k \quad -------(5)$$

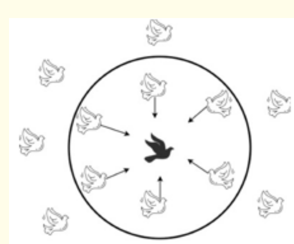

Figure 2: Illustration of historical operator model of PIO.

As shown in figure 2, the center of all the pigeons (the pigeon in the center of the circle) represent the right destination at each iteration. Half of the pigeons (pigeons outside the circle) that are far from their destination will follow the pigeons close to their destination, which also means that two pigeons can be in the same place. Pigeons close to their destination (the pigeons in the circle) will fly very quickly to get to their destination [9].

Basic procedure of PIO

PIO algorithm

The steps involved in the computer-simulated sequence of execution of PIO can be expressed as follows:

- **Step 1:** initialize the parameters of the PIO algorithm, such as the dimension of the solution space D, the size of the population Np, the map and the compass factor R, the number of iterations Nc1 max and Nc2 max for two operators, and Nc2 max> Nc1 max.
- **Step 2:** Define each pigeon with a random speed and path. Compare the physical condition of each pigeon and find the best current path.
- **Step 3:** Activate the operator of the compass card. First, we update the speed and path of each pigeon using Eq. (1) and Eq. (2). Then we compare the fitness of all the pigeons and find the new best path.
- **Step 4:** If Nc> Nc1 max, stop the operator of the compass card and activate the next operator. Otherwise, go to step 3.
- **Step 5:** Classify all the pigeons according to their physical values. Half of the pigeons with poor physical condition will follow the pigeons with high physical condition in accordance with Eq. (3). We then find the center of all pigeons according to Eq. (4), and this center is desirable.
- Destination. All pigeons will fly to the destination by adjusting their direction of flight according to Eq. (5). Then store the best solution parameters and the best cost value.
- **Step 6:** If Nc<Nc2 max, stop the benchmark operator and display the results. Otherwise, go to step 5 [9,13].

The above steps can be summarized as a pseudocode:

Input parameters

- NP: Number of individuals in a swarm of pigeons
- D: Size of the search space
- A: The compass map operator
- Search area: The limits of the search area
- Nc1max: Maximum number of generations for which the map and the compass are used
- Nc2max: Maximum number of generations of execution of the operation.
- T: The threshold of lateral inhibition.

Output parameter

Xg: the global optimum of the fitness function f.

Initialization

Define the initial values for Nc1max, Nc2 max, NP, D, R and the search area

Define the initial path Xi and the velocity Vi for each pigeon

Define Xp = Xi, Nc = 1

Calculate the fitness values of different pigeons.

$$X_g = \text{argmin}[f(X_p)]$$

Map and compass operators

For Nc = 1 to Nc1max do

For i = 1 at Np do

While Xi is beyond the search range do

Calculate Vi and Xi according to Eq. (1) and Eq. (2)

End while

End for

Evaluate Xi and update Xp and Xg

End for

Historic operators

For Nc = Nc1max to Nc2max, do

While Xp is beyond the search range do not classify all available pigeons according to their physical values

NP = NP = 2 keep half of the individuals with better physical value and abandon the other half Xc = average value of the paths of the other pigeons

Calculate Xi according to Eq. (4)

End while

Evaluate Xi and update Xp and Xg

End for

Exit

Xg: is the output as a global optimum of the fitness function f [14,15].

Coding and objective function

In order to establish a PIO classifier for the supervised classification of remote sensing images, including the coding of pigeon chains, one must define the objective function, and execute the operators of the OPI algorithm.

Coding of pigeons

In PIO applications, the parameters of the search space are coded in the form of a chain, called pigeon, representing a solution to the problems. In this article, a pigeon is coded with a set of positive integers; each unit represents a class center. Take the following example. Assuming we have a satellite image. From the set of calculated samples, we created the initial population set.

In order to obtain a selected population rate, we built a list of individuals according to size (Number of pigeons at the entrance)

Pigeons	**R_1**	**G_1**	**B_1**	**R_2**	**G_2**	**B_2**	**.**	**R_n**	**G_n**	**B_n**
P_1	$r_{1,1}$	$g_{1,1}$	$b_{1,1}$	$r_{1,2}$	$g_{1,2}$	$b_{1,2}$	.	$r_{1,n}$	$g_{1,n}$	$b_{1,n}$
P_2	$r_{2,1}$	$g_{2,1}$	$b_{2,1}$	$r_{2,2}$	$g_{2,2}$	$b_{2,2}$	.	$r_{2,n}$	$g_{2,n}$	$b_{2,n}$
P_3	$r_{3,1}$	$g_{3,1}$	$b_{3,1}$	$r_{3,2}$	$g_{3,2}$	$b_{3,2}$	.	$r_{3,n}$	$g_{3,n}$	$b_{3,n}$
.	.	.	.	.	.	.	.	.	.	.
.	.	.	.	.	.	.	.	.	.	.
.	.	.	.	.	.	.	.	.	.	.
P_k	$r_{k,1}$	$g_{k,1}$	$b_{k,1}$	$r_{k,2}$	$g_{k,2}$	$b_{k,2}$		$r_{k,n}$	$g_{k,n}$	$b_{k,n}$

Table 1: The initial population set.

each pigeon is considered as a vector.

Then we generated an *Xg* food center, the one with optimal fitness (Minimum) Calculation of the distance between the class means:

Xg = (R1, G1, B1, R2, G2, B2… Rn, Gn, Bn) fit min

Objective function

The PIO algorithm maintains a solution based on an objective function which is associated with each pigeon which represents the quality of the pigeon. Several indices of validity of the classification have been developed to determine an optimal classification; in this article we have used the Davies-Bouldin Index "DBI» [2].

DBI has been adopted as an objective function due to its suitability for remote sensing images.

$$\mu ki = \begin{cases} 1, \text{argmin } \|Xi, Cj\| = K \\ 1 < j < n \\ 0, \text{otherwisef} \end{cases} \qquad \text{---------(5)}$$

	Member ships function of pixel to class k
Xi	The gray level of pixel i
	The number of elements in class K
Xk	All elements of class k
V	The average
S	Standard deviation

Table 2: The parameters to calculate the DBI function.

$$Vk = \frac{\sum_{i=1}^{Mk}(\mu ki)Xi}{\sum_{i=1}^{Mk}(\mu ki)} = \frac{\sum_{Xi \in Xj} Xi}{Mk} \qquad \text{--------- (6)}$$

$$Sk = \left(\frac{1}{Mk}\sum_{x \in Xi} \|X - Vk\|^2\right)^{1/2} \qquad \text{--------- (7)}$$

w

$$dkj = \|Vk - Vj\| \qquad \text{---------(8)}$$

dkj is the Minkowski distance of order t between the Kth center and the ith center. We set t = 2 Then the value Rk of the center kth is calculated by equation.

$$Rk = \max \frac{Sk + Sj}{dkj} \qquad \text{------(9)}$$

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

$$DB = \frac{1}{n}\sum_{k=1}^{n} R_k \qquad \text{-------- (10)}$$

Experimental Results and Discussion

A sophisticated satellite landscape image is used to test the performance of the three proposed algorithms on image complexes. We have an image of Oran Ouest given by the LANDSAT TM satellite of March 15, 2016, acquired from the Center de Techniques Spatiales CTS in Arzew (Oran). This image was chosen for the diversity of the themes that compose it. The channels used are: red, infrared and blue. In our application, we have chosen a study region of size 1443 × 1080, (area shown in Figure 3). The latter is made up of 10 themes: C1: Sea, C2: Surf, C3: Sand and sol, C4: Market gardening, C5: Fallow, C6: Forest, C7: Maquis, C8: Urban, C9:Sebkha1 and C10:Sebkha2.

Classification

The performance of these algorithms depends on a number of parameters, the values of which may or may not depend on the image to be classified. All these parameters have been chosen empirically, that is to say by trial and error, until the good results were obtained. The values of these parameters change from one image to another and there is no formula for determining the optimal values.

Classification results of the study area (satellite image)

This section presents the different classification tests and the

Figure 3: Oran TM image.

results obtained by the three algorithms (PIO, k-means bisecting, and deep learning) on the SAT image used.

Result of the Pigeon algorithm

For these tests we fixed the parameters of the Pigeon algorithm under the following values.

N	NCmax	NC1max	NC2max	R	D	T
200	150	100	50	0.2	2	115

Table 3: Parameters of the Pigeon algorithm.

The following figure illustrates the result of the classification with the variation in the number of generations. The confusion matrix corresponding to the best result obtained.

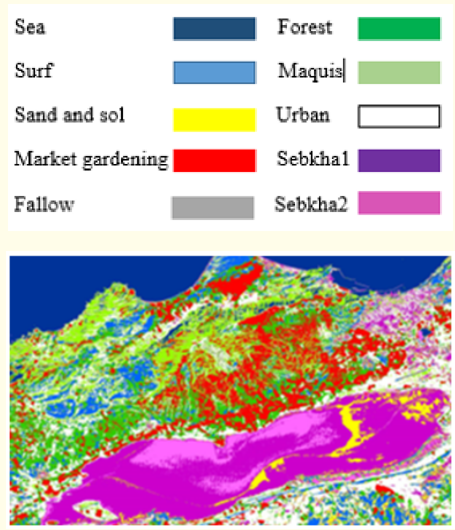

Figure 4: Image classified by Pigeon Algorithm with a selection rate of 90.

Classes	C1	C2	C3	C4	C5	C6	C7	C8	C9	C10
C1	99,98	0	0	0	0	0	0	0	0	0
C2	0	100	0	0	0	0	0	0	0	0
C3	0	0	91,68	0	0	0	0	0	0	0
C4	0	0	0	90,7	0	0	0	0	0	0
C5	0,01	0	0	0	99,99	0	0	0	0	0
C6	0	0	0	0	0	93,37	0	0	0	0
C7	0	0	0	0	0	0	95,98	0	0	0
C8	0	0	0	0	0	0	0	92,46	6,87	1,23
C9	0	0	8,3	9,28	0	0	0	1,76	93,1	0
C10	0	0	0	0	0	6,6	4,01	5,75	0,01	98,75

Table 4: Confusion matrix relating to the image classified by the Pigeon algorithm with a classification rate: 95.60%.

This result shows the efficiency and the feasibility of the PIO algorithm for the classification of this type of image. Despite the presence of confusion between classes such as the forest class and the sebkha2 class, the pixels of the sebkha2 class were assigned to the forest class, another confusion between sebkha2 and urban and sekbha 1 and market gardening We recorded a good ranking rate equal to 95.60%.

Classification rate	95.60%
Accuracy	84.70%
Reminder	21.40%
F-measure	34.00%
Exécution time	19.15 sec

Table 5: The average of the results obtained PIO ten classes.

Using the PIO algorithm, we obtained a good classification rate with an average execution time of 19.15 s which is better compared to the methods compared and a recall of 21.40%. We also notice that the PIO is more precise with a rate of 84.70%.

Result of the K-Means Bisecting algorithm

In order to compare the PIO method with the k-means bisecting method we have applied the latter on Oran TM image and we have set the parameters of the K-Means Bisecting algorithm under the following values:

Setting	Description	Parameter values
Niter	Nember of iterations	500
K	Nember of cluster	10
Ssw	Within cluster variance	
Ssb	Between cluster variance	
Wbi	F-ratio index for partition of clusters	

Table 6: Parameters of the K-Means Bisecting algorithm.

The following figure illustrates the classification result with the variation in the number of generations. The confusion matrix corresponding to the best results obtained.

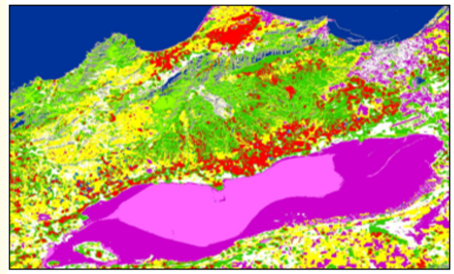

Figure 5: Image classified by K-Means Bisecting Algorithm.

K(Cluster)	SSW	SSB	WBI
2	31544,0037	4268787,83	0,0147789
3	15652,6793	3850591,93	0,01219502
4	12377,3373	3263457,82	0,01517083
5	12488,2191	3247765,78	0,01549207
6	2831,65858	2211655,73	0,00326165
7	4940,92152	3136304,81	0,00735117
8	12581,0617	3133496,32	0,01610514
9	6117,3264	6855624,96	0,00139732
10	8119,42854	6138234,33	0,00865416

Table 7: Values of SSW, SSB and WBI obtained from each cluster.

Classes	C1	C2	C3	C4	C5	C6	C7	C8	C9	C10
C1	100.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0
C2	0.0	96.19	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0
C3	0.0	0.0	94.99	0.0	0.0	0.0	0.0	0.0	0.0	0.0
C4	0.0	0.0	0.0	84.61	0.0	0.0	0.0	0.0	0.0	0.0
C5	0.0	0.0	0.0	0.0	97.96	0.0	0.0	0.0	0.0	0.0
C6	0.0	0.0	0.0	1.27	0.0	87.65	0.0	0.0	0.0	0.0
C7	0.0	0.0	0.0	0.0	2.02	0.0	99.99	0.0	0.0	0.0
C8	0.0	0.0	0.0	0.0	0.0	0.0	0.0	88.36	1.84	11.57
C9	0.0	3.78	4.99	14.08	0.0	11.53	0.0	2.18	98.13	0.0
C10	0.0	0.0	0.0	0.0	0.0	0.79	0.0	9.41	0.0	88.41

Table 8: Confusion matrix relating to the image classified by k-means bisecting with a classification rate: 93.63%.

This result shows the presence of chauvochism between classes like the urban class and the sebkha2 class, the pixels of the first class were assigned to the second class, sebkha1 and sand and so and also another chauvochism between sebkha 1 and market gardening. We recorded a classification rate equal to 93.63%

Classification rate	93.63%
Accuracy	74.60%
Reminder	07.70%
F-measure	13.80%
Exécution time	122.878 sec

Table 9: The average of the results obtained k-means bisecting ten classes.

When we apply the k-means bisection algorithm in the classification of sat images, we get a classification rate of 93.63% which is lower than that of OPI in a longer average runtime 122.878 dry, and we also notice that it is less precise with a rate equal to 74.60% and a reminder of 07.70%

Result of the deep learning algorithm

In order to compare the PIO method with the deep learning method, we applied the latter on the Oran TM image and we defined the parameters of the algorithm under the following values.

Relu	Convolution	Poling
5	3x3	2x2

Table 10: Parameters of the deep learning algorithm.

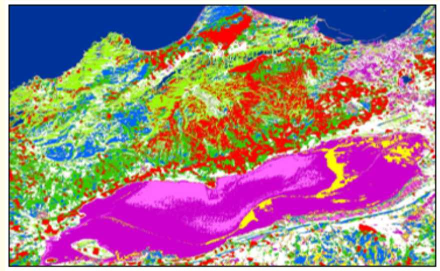

Figure 6: Image classified by Deep learning Algorithm.

Classes	C1	C2	C3	C4	C5	C6	C7	C8	C9	C10
C1	95,95	0	0	0	0	0	0	0	0	0
C2	0	99,96	0	0	0	0	0	0	0	0
C3	0	0	88,6	0	0	0	0	0	0	0
C4	0	0	0	99, 98	0	0	0	0	0	0
C5	4,04	0	0	0	99,96	0	0	0	0	0
C6	0	0	0	0	0	99,97	0	0	1,03	0
C7	0	0	0	0	0	0	94,21	4,93	0	0
C8	0	0	0	0	0	0	0	94,86	0	8,82
C9	0	0	11,37	0	0	0	0	0	98, 93	0
C10	0	0	0	0	0	6,6	4,01	0	0	91,16

Table 11: Confusion matrix relating to the image classified by deep learning with a classification rate: 96.53%.

This result shows a certain confusion rate between the classes, as between the class sebkha1 and the class sand and sol, the class sebkha 2 and the class urban as well as sebkha 2 and the maquis class we obtained a ranking of 96.53%

Classification rate	96.53 %
Accuracy	70.06 %
Reminder	19.60 %
F-measure	30.40 %
Exécution time	410.11 sec

Table 12: The average of the results obtained deep learning ten classes.

Using the deep learning algorithm, we got a good rank rate of 96.53% over longer run time of 410.11s, accuracy of 70.06%, and recall of 19, 60%. On note that in terms of precision and execution time the OPI algorithm is better.

Conclusion

Content Based Image Classification is important for improving the Accuracy of Image Retrival. This article aims is to classify satellite images using the PIO algorithm, inspired by the natural behavior of pigeons foraging for food. To assess its performance and efficiency, we compared the results obtained by the PIO algorithm with those obtained by the k-means bisecting and Deep Learning algorithm. Using the PIO algorithm, we got a rank rate of 95.60% with an average run time of 19.15sec, accuracy of 84.70%, and recall of 21.40%. It is an efficient algorithm that leads to better results than those obtained by the k-means bisecting algorithm with a classification rate of 93.63% an execution time of 122.878sec, an accuracy of 74.60% and a recall of 07.70%. of the PIO algorithm are close to those obtained by the deep learning algorithm with an average classification rate of 96.53% in a longer execution time of 410.11 sec with an accuracy of 70.06% and a recall of 19.60%.

Bibliography

1. U Maulik and D. Chakraborty. "Remote Sensing Image Classification: A survey of support-vector-machine-based advanced techniques". *IEEE Geoscience and Remote Sensing Magazine* 5.1 (2017): 33-52.

2. A M Hannane and H Fizazi. "Supervised images classification using metaheuristics". *Mathematical and Computer Modelling* (2016): 7.

3. N Liu., *et al*. "Exploiting Convolutional Neural Networks With Deeply Local Description for Remote Sensing Image Classification". *IEEE Access* 6 (2018): 11215-11228.

4. G Cheng., *et al*. "When Deep Learning Meets Metric Learning: Remote Sensing Image Scene Classification via Learning Discriminative CNNs". *IEEE Transactions on Geoscience and Remote Sensing* 56.5 (2018): 2811-2821.

5. D Ienco., *et al*. "Land Cover Classification via Multitemporal Spatial Data by Deep Recurrent Neural Networks". *IEEE Geoscience and Remote Sensing Letters* 14.10 (2017): 1685-1689.

6. H M Ahmed., *et al*. "Hybrid gray wolf optimizer-artificial neural network classification approach for magnetic resonance brain images". *Applied Optics* 57.7 (2018): B25.

7. S Sharma and K M Buddhiraju. "Spatial-spectral ant colony optimization for hyperspectral image classification". *International Journal of Remote Sensing* 39.9 (2018).

8. H Duan and X Wang, "Echo State Networks With Orthogonal Pigeon-Inspired Optimization for Image Restoration". *IEEE Transactions on Neural Networks and Learning Systems* 27.11 (2016): 2413-2425.

9. H Duan and P Qiao. "Pigeon-inspired optimization: a new swarm intelligence optimizer for air robot path planning". *International Journal of Intelligent Computing and Cybernetics* 7.1 (2014).

10. W Liu., *et al*. "An Improved Otsu Multi-Threshold Image Segmentation Algorithm Based on Pigeon-Inspired Optimization". in 2018 11th International Congress on Image and Signal Processing, BioMedical Engineering and Informatics (CISP-BMEI), Beijing, China (2018): 1-5.

11. C Davison., *et al*. "Magnetoreception and its trigeminal mediation in the carrier pigeon". *Nature* 432.7016 (2004): 508-511.

12. Q Luo and H Duan. "Distributed Drone Flocking Control Based on Hierarchical Carrier Pigeon Strategies". *Aerospace Science and Technology* 70 (2017): 257-264.

13. H Liu., *et al*. "An Improved Pigeon-Inspired Optimization Algorithm and Its Application in Parameter Inversion". *Symmetry* 11.10 (2019): 1291.

14. AL Bolaji., *et al*. "Adaptation of Binary Pigeon-Inspired Algorithm for Solving Multidimensional Knapsack Problem". in Soft Computing: Theories and Applications 583, M. Pant, K. Ray, T. K. Sharma, S. Rawat, and A. Bandyopadhyay, Eds. Singapore: Springer Singapore (2018): 743-751.

15. Y Zhong., *et al*. "Discrete pigeon-inspired optimization algorithm with Metropolis acceptance criterion for large-scale traveling salesman problem". *Swarm and Evolutionary Computation* 48 (2019): 134-144.

Assets from publication with us

- Prompt Acknowledgement after receiving the article
- Thorough Double blinded peer review
- Rapid Publication
- Issue of Publication Certificate
- High visibility of your Published work

Website: www.actascientific.com/
Submit Article: www.actascientific.com/submission.php
Email us: editor@actascientific.com
Contact us: +91 9182824667