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Metaheuristic Honey Badger Optimization for Remote Sensing Image Clustering

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ABSTRACT

In this paper, we demonstrate satellite image classification by the algorithm optimized with HBA (Honey Badger Algorithm). This approach leverages the Honey Badger Algorithm's unique foraging behavior to effectively group pixels with similar spectral characteristics, thus enhancing the interpretability of complex remote sensing data. This novel application aims to address the limitations of traditional clustering methods in handling the high dimensionality and intricate spatial patterns inherent in remote sensing imagery. The satellite image is tested using the method. The experimental results demonstrated that the convergence speed and the performance of the algorithm are satisfactory.

Keywords: Clustering, Honey Badger algorithm, Satellite image, Remote sensing, Metaheuristics.

INTRODUCTION

Processing images is a broad scope and is an evolving field. Not only does it involve replacing a human observer with a machine, it is fields of technology evolving very rapidly.

Image clustering is the search for distinct groups for a given set of attributes in feature space. These distinct groups would ideally differ from one another and would have a structure that would allow them to be easily differentiated. The clustering task separates the data into a predefined number of subsets, which are regions in the n-dimensional feature space. The hard limit that exists between the groups is defined by the functions used to model data distribution. These partitions are ndimensional and the clustering task delineates the number of partitions. These partitions are defined by hard limits and are determined based on the functions used to model data distribution [1].

A number of artificial intelligence techniques have been used to perform clustering for satellite images, majority of which are optimization techniques. The problem of clustering is defined as an optimization problem that needs to be solved in order to realize these techniques. To achieve set goals, a problem is defined and parameters are set to be adjusted in order to reach predetermined optimal values. This is what optimization in a general sense is. [2].

The past few years have seen renewed interest in developing many different metaheuristic optimization algorithms, which is a novel approach in numerical optimization. Metaheuristics are optimization algorithms that are inspired by nature, and have been proven efficient to work on a wide spectrum of problems.

There are two main classes of meta-heuristics [3]. The first one consists of the meta-heuristics which evolve a single solution on the search space and the second. The single solution strategies include Tabu Search Algorithm (TSA) [4] and Simulated Annealing (SA) [5]. The population-based methods are more exploratory and provide better diversity in the search space such as genetic algorithms (GA) [6] and Cuckoo Search Algorithm (CSA) [7].

The use of the meta-heuristic algorithm is gaining importance in research for image processing, especially in satellite image classification [8]. There is considerable research employing meta-heuristic approaches such as Genetic Algorithms (GA) [9], Particle Swarm Optimization (PSO) [10], Ant Colony Optimization (ACO) [11], Grasshopper Optimization Algorithm (GOA) [12], Harmony Search (HS) [13], Dragonfly Algorithm (DA) [14], Bat inspired Algorithm (BAT) [15], Ant Lion Optimization (ALO) [16], and Eagle Strategy [17].

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In this paper, we aim to optimize clustering using one of these metaheuristic algorithms, namely the Honey Badger Algorithm (HBA) to classify satellite images.

The primary objective of this study is to analyze the potential of Honey Badger Algorithm using remotely sensed data. The performance of HBA is compared against other algorithms such as Genetic algorithm, Ant Colony Optimization and Particle swarm optimization.

The article is structured as follows. Section II presents a detailed description of the methods. Satellite images used for the experiments, obtained results, and comparative studies are presented in section III. Section IV concludes the paper.

METHODS

2.1 HONEY BADGER ALGORITHM

In 2021, Fatma A. Hashima et al. proposed the honey badger algorithm (HBA), a novel kind of intelligent optimization algorithm that primarily aims for optimization by mimicking the honey badger's natural hunting behavior.

The intelligent feeding behavior of badgers serves as the foundation for the HBA class of metaheuristic optimization algorithms, which mathematically create an effective search strategy to address the optimization problem. Hashim et al [18].

Fig. 1. The Honey badger

Mammals with black, fluffy, and white fur, honey badgers are typically found in southwestern Asia, the Indian subcontinent, and semi-arid and African rainforests.

Since their cubs can be born at any time of the year, honey badgers do not have a specific breeding season. The first step is to use excavation to determine the prey's approximate location, and then the prey is captured. Although it could be more adept at locating beehives, the honey badger prefers honey. These encounters create a mutually beneficial relationship between the badger and the bird, whereby the badger uses its long claws to help the bird open the hives and the bird leads the badger to the beehives. Below is a description of the algorithm's different steps.

The Honey Badger Algorithm (HBA) mimics how honey badgers would search. The honey badger follows the honeyguide bird or sniffs and digs to find the food source. Digging mode is the term for the first scenario, and honey mode is the term for the second [19]. In the first mode, it approaches the prey's location by using its sense of smell. Once there, it maneuvers around the prey to select the best spot to dig and seize it. In the second mode, the honey badger locates the beehive by following the honeyguide right away (see Fig. 2).

Fig. 2. Relationship between honey badger and honey guide

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2.2 MATHEMATICAL MODEL

The digging phase and the honey phase are the two stages of HBA, as was previously mentioned. The steps of the suggested HBA are broken down mathematically as follows: In HBA, the population of potential solutions is shown as follows:

$$X=\begin{bmatrix} x_{11} & x_{12} & \cdots & x_{1D} \\ x_{21} & x_{22} & \cdots & x_{2D} \\ \cdots & \cdots & \cdots & \cdots \\ x_{n1} & x_{n2} & x_{n3} & x_{nD} \end{bmatrix} \quad (1)$$

i-th position of the honey badger $x_i = [x_i^1, x_i^2, \ldots, x_i^D]$ (2)

Step 1: Initialization phase: Set the population size (N) of badgers and their locations in accordance with the equation. (3):

$$x_i = lbi + r1 \times (ubi - lbi), \; r_1 \in [0, 1] \quad (3)$$

Where lbi and ubi represent the lower and upper bounds of the search domain, respectively, and xi is the ith honey badger position pointing to a candidate solution in the N population.

Step 2: Intensity definition: The strength of the prey's concentration and the distance between it and the i-th honey badger determine intensity (I). Ii is the prey's scent intensity; slow motion results from a low scent and vice versa. The inverse square law (ISL) provides it.

$$I_i = r_2 \times \frac{S}{4\pi d_i^2}, \; r_2 \in [0, 1] \quad (4)$$

$$S = (x_i - x_{i+1})^2 \quad (5)$$

$$d_i = x_{prey} - x_i \quad (6)$$

Where S stands for the source force or the force of concentration. As in (2), Fig. 3's di denotes the distance between the prey and the i-th honey badger.

Step 3: Update the density factor. The density factor (α) regulates time-varying randomness to guarantee a smooth transition from exploration to exploitation. To reduce randomization over time, update the decreasing factor (α), which decreases with iterations, as in (7).

$$\alpha = C \times \exp(-t/tmax) \quad (7)$$

Where tmax is the maximum number of iterations and (C) is a constant number greater than 1 (by default, it is 2).

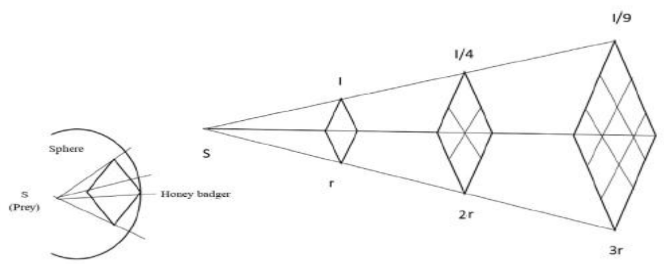

Fig. 3: Inverse square law. I is smell intensity, S is location of prey, and r is random number between 0 and 1.

Step 4: Escaping from local optimum. The current step and the two next ones are used in the HBA to escape from local optima regions. The proposed algorithm uses the F flag that changes the search direction to provide high opportunities for agents to scan the search area precisely.

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Step 5: Updating the agents' positions. As mentioned earlier, the process of updating the HBA position (x_{new}) is divided into two stages: the "digging phase" and the "honey stage". Following is a more detailed description:

Step 5-1: Digging phase. In digging stage, the honey badger performs a similar action to Cardioid shape [2] as shown in Fig. 4. Using (8) to simulate Cardioid movement.

$$x_{new} = x_{prey} + F \times \beta \times I \times x_{prey} + F \times r_3 \times \alpha \times d_i \times |\cos(2\pi r4) \times [1 - \cos(2\pi r5)]| \quad (8)$$

Where x_{prey} is the best position of the prey found so far in other words the global best position.

$\beta \geq 1$ (default = 6) is ability of the honey badger to find food. r_3, r_4, and r_5 are three different random numbers between 0 and 1. F works as the flag that changes search direction, by using (9):

$$F = \begin{cases} 1 & \text{if } r_6 \leq 0.5 \\ -1 & \text{else,} \end{cases} \quad r6 \in [0, 1], \quad (9)$$

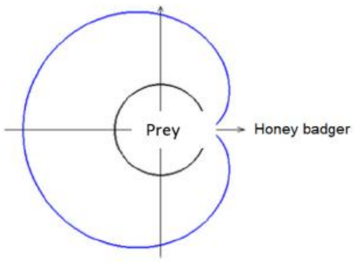

Fig. 4: Digging phase

In Fig.4, the blue outline indicates the strength of the smell, while the black circular line indicates the position of the prey.
In the digging phase, a honey badger is highly dependent on smell intensity I of prey x_{prey} , distance between the badger and prey di , and time-varying search influence factor α. Moreover, during digging activity, the badger honey may receive any disturbance F allowing it to find a better location for prey (see Fig. 4).

Step 5-2: Honey phase. In Honey stage, the honey badger follows, honey guide bird to a beehive can be simulated as (10):

$$x_{new} = x_{prey} + F \times r_7 \times \alpha \times d_i, \quad r7 \in [0, 1] \quad (10)$$

Where x_{new} is the new position of honey badger, whereas x_{prey} is prey location, Equations (7) and (9) determine the value of (α) and (F), respectively. From (10), it can be observed that a honey badger proceeds search close to prey location x_{prey} found so far, depending on distance information di. At this point, the search behavior that changes over time (α) affects the search. The honey badger may also an experience perturbation (F).

The steps of the Honey Badger algorithm are illustrated as:

- Set parameters : t_{max} , N, β,C.
- Initialize population with random positions.
- Evaluate the fitness of each honey badger position x_i using objective function and assign to f_i , i ∈ [1, 2, ..., N].
- Save best position x_{prey} and assign fitness to f_{prey}.
- while t ≤ tmax do
- Update the decreasing factor α using (7).
- for i = 1 to N do
- Calculate the intensity Ii using (4).
- if r < 0.5 then ; r ∈ [0, 1]
- Update the position x_{new} using (8) (Digging Phase).

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- else
- Update the position x_{new} using (10) (Honey Phase).
- end if
- Evaluate new position and assign to f_{new}.
- if $f_{new} \leq f_i$ then
- Set $x_i = x_{new}$ and $f_i = f_{new}$.
- end if
- if $f_{new} \leq f_{prey}$ then
- Set $x_{prey} = x_{new}$ and $f_{prey} = f_{new}$.
- end if
- end for
- end while Stop criteria satisfied.
- Return the best solution: f_{prey} and x_{prey}.

RESULTS AND DISCUSSION

We tested our method on a satellite images. These tests were carried out by Honey Badger algorithm(HBA).
In order to obtain the best optimization results by the HBA algorithm, the selection of parameter values is important because these parameters can seriously affect the performance of this algorithm. After several tests, the population size and the maximum number of iterations for both the algorithms are set to 50 and 150 respectively. Other parameters such as dimension were considered for the objective function.
In our work, the objective function to be optimized is the intra-class inertia also called the quadratic error function since we used the Euclidean distance as a measure of similarity and the stopping criterion is the maximum number of iterations.
The procedures of our classification were tested on digitized data from Sentinel 2-L2A satellite images of the Bouhanifia region, located approximately 400 km west of Algiers (ALGERIA), acquired on August 16, 2019 of 400 x 400 pixels with a spatial resolution of 30. (Fig. 5).

Fig. 5. Satellite image used

The objective of the following experiments is to measure the quality of our HBA algorithm for unsupervised classification of remote sensing images.

The influence of the variation in the number of iterations on the results obtained; when we increase the number of iterations, the better classification (T = 150), but reaching a certain number of iterations (T = 200) the performance of our algorithm begins to degrade. This degradation is due to the density factor (α) which controls the randomization (r3) over time.
For the other tests, we varied just the number of clusters (K) in order to evaluate its contribution to the quality of the classification. The different results obtained are summarized in the table below (Table 1 and Fig. 6)

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Table 1. Result of unsupervised classification by the HBA algorithm on the satellite image.

Nbr_clusters (K)	4	5	6	7	8
Fitness	4210008.5024	3255774.2229	**2180665.9181**	3911185.1470	3820025.9157
DBI index	0.9527	1.8123	**0.84071**	0.95176	0.92884
Execution time	13.564108s	35.330887s	**95.358746s**	136.852371s	214.282083s

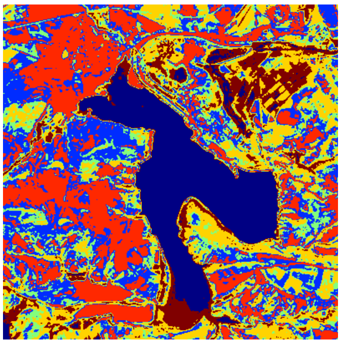
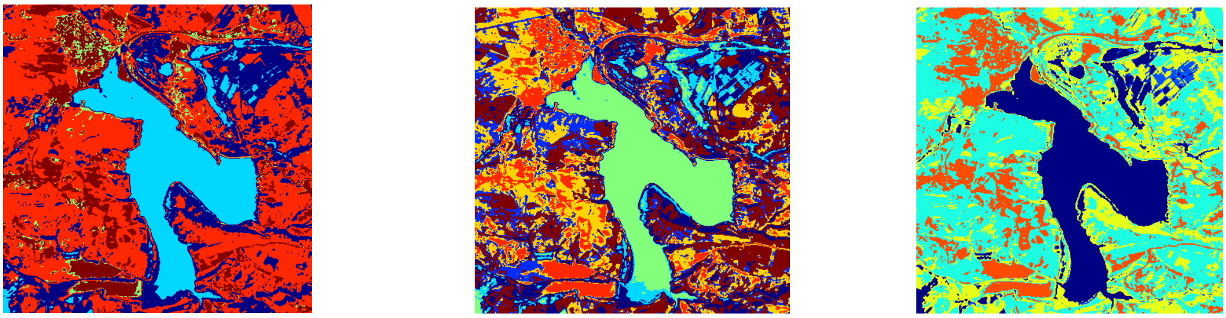


Fig. 6. Results of unsupervised classification by the HBA algorithm (K=6)

From Table 1, it can be noticed that the HBA is a totally stable algorithm and tends to minimize the DBI value (DBI=0. 84071) to the optimum clusters (K=6).
For the last test, we used the satellite image (Fig. 5). For this experience we used the best parameters of Honey Badger algorithms (T=150, N=6) and it then compared with three methods, such as Genetic algorithm (GA)[21], Particle swarm optimization PSO [22] and Ant Colony Optimization (ACO)[23] .
At this level, we will compare the HBA algorithm with GA, PSO and ACO in terms of global minimal values and execution times according to the different tests performed (Table 2, Fig.7).



(a): GA (b):PSO (c):ACO

Fig. 7. Results of unsupervised clustering on a satellite image by (GA, PSO and ACO) algorithms

Table 2. The results of the satellite image clustering by the four algorithms

	HBA	GA	PSO	ACO
Means	1.2473+e05	5.9422+e05	3.1755+e06	6.1171+e05
Execution time	90.485 s	185.627 s	113.258 s	143.182 s

Table2 shows that the performances of HBA have outperformed those of the other three algorithms as follows: GA, PSO and ACO.

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The means of HBA Algorithm were 1.2473+e05, which is much less than the means in the other algorithms. This indicates that the better means produced by the proposed method are statistically significant.
It should be noted that all of these algorithms use the same memory size, but their run time are different. The HBA takes about 90.485 s, while the GA, PSO and ACO take 185.627 s 113.258 s and 143.182 s, respectively.
It is obvious that HBA achieves the best performance than others, which means that HBA is better than GA, PSO and ACO for solving image clustering problems.

CONCLUSION

The results discussed in this paper demonstrated the effectiveness of the HBA in the classification of satellite images; the results of this classification were efficient in terms of the objective function value, and execution time. This algorithm also stands out for its ability to make automatic classification.
The HBA is sensitive to two parameters: the number of iterations and the number of clusters that are tested on satellite images. The comparative results of HBA, GA, ACO and PSO shows that the classification based on HBA is the best in terms of execution times and global minimum. It also allowed a better discrimination between the themes having strong similarity.
We believe that this work can be complemented by evaluation on other databases as well as on other types of data. In addition, it would be interesting to add other data sources, such as slope or radar.

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