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AEO-HGO Adaptive Exploration-Exploitation Hybrid Gas Optimization for Satellite Image Segmentation

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Abstract

In recent years, the fast dispensation of high-resolution color satellite images, which is made possible by remote sensing technology, has develop a vital need in key claims such as environmental monitoring, urban planning, and disaster management among other uses. The reason for this is that these apps are very necessary for the success of these applications. Color satellite imaging provides a plethora of information, which enables a more in-depth investigation of land use, plant cover, and other surface features. This is made possible by the use of high-resolution satellite images. In this regard, it is worth noting that there is a vast amount of usage of multi-level image thresholding techniques in an effort to improve the quality of the segmentation process. However, it is worth noting that achieving high accuracy and low processing costs simultaneously in complex scenarios is still a major challenge. This article presents a unique adaptive hybrid optimization technique that is referred to as AEO-HGO. The goal of this optimization method is to address the challenges. The optimization method that has been presented includes a stage of global search that is conducted through the population search, as well as the local search strategy. For the purpose of color multi-level satellite image thresholding, the findings have revealed that the AEO-HGO method has the advantage of providing a solution that is stable, scalable, and computationally efficient. Real-world applications, such as catastrophe management, agricultural monitoring, and urban planning, could potentially benefit from the application of this technique.

Keywords: Color satellite image segmentation, multi-level thresholding, Hybrid optimization algorithm, Adaptive exploration-exploitation, Remote sensing image analysis, High-resolution satellite imagery

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1. Introduction

With the recent spate of advancements in the development of remote sensing technology, an unprecedented rise in the availability of satellite images of high resolution and in color has brought about a paradigm shift in the analysis and interpretation of the Earth's surface. Satellite images are an essential source of data in a variety of fields, such as environmental studies, urban planning, agricultural management, and disaster relief. Due to the complexity of satellite data, there is a growing need to develop accurate, efficient, and scalable image processing techniques that are capable of extracting valuable information from this complex visual data [1].

Among the most fundamental problems associated with the analysis of satellite images is the problem of image segmentation, which is the task of dividing an image into significant regions that correspond to different land cover types or surface characteristics. Image segmentation is an important step that facilitates various analyses such as land use classification, vegetation mapping, infrastructure identification, and change detection analysis. In this regard, multi-level thresholding has been identified as one of the most widely used segmentation techniques because of its simplicity and efficiency in handling different types of images. Multi-level thresholding is a technique that involves the selection of several intensity thresholds that divide an image into a number of distinct regions [2].

Color satellite images pose distinct and challenging problems for multi-level thresholding techniques. Unlike grayscale images, color images possess information that lies in multiple spectral bands, thus increasing the dimensionality of the thresholding task. Furthermore, the variability of natural and artificial surface characteristics, such as forests, water, urban areas, agricultural regions, and bare soil, requires that image segmentation techniques preserve high discriminative capability and efficiency. As the number of threshold levels rises, the search space expands exponentially, making it unfeasible to apply exhaustive search strategies and thus providing a rationale for the application of metaheuristic optimization approaches [3].

Over the past ten years, a wide range of nature-inspired and population-based optimization techniques has been explored for the image thresholding task. Although these algorithms have shown promising performance, they are often prone to well-known issues such as premature convergence to local optima, parameter sensitivity, slow convergence speed in high-dimensional search spaces, and an unbalanced exploration-exploitation trade-off. These issues become even more challenging to handle when working with complex multi-channel color satellite images [4] at higher thresholding levels, where both performance and efficiency are of utmost importance [5][6].

To overcome these challenges, this paper proposes the Adaptive Exploration-Exploitation Hybrid Gas Optimization (AEO-HGO) algorithm, a new hybrid metaheuristic approach tailored to the color multi-level satellite image thresholding problem. The AEO-HGO algorithm combines a population-based global exploration process with an adaptive local exploitation approach, allowing the algorithm to adaptively strike a balance between exploring the solution space and exploiting potential solutions with high accuracy. This adaptive balance process helps to improve the diversity of solutions, speed up convergence, and improve the robustness of the results.

2. Related work

The issue of image segmentation using multi-level thresholding has received much attention in the community of remote sensing and computational intelligence. Several different approaches based on optimization have been proposed to deal with the complexity of choosing optimal threshold values, especially in high-dimensional color images.

Mirjalili et al. [7] suggested the use of the Grey Wolf Optimizer (GWO) for multilevel image thresholding based on Kapur's entropy and Otsu's between-class variance. The authors showed that GWO provided a competitive level of segmentation accuracy compared to PSO and GA on common benchmark images, but with a faster convergence rate. Nevertheless, the algorithm performed poorly for larger threshold values because of the complexity of the search space, which is a drawback that requires the design of more adaptive approaches, as done in this study.

Bhandari et al. [8] explored the application of Differential Evolution (DE) for multilevel thresholding of remote sensing images, using Tsallis entropy as the fitness measure. The study showed that DE performed better than the conventional gradient-based approaches in terms of image segmentation quality, especially for images with complex and non-uniform intensity distributions, as observed in satellite images. However, the sensitivity of DE to its control parameters was also highlighted, which emphasizes the importance of self-adaptive approaches in optimization-based image segmentation techniques.

The basic concept of variance-based thresholding was introduced by Otsu et al. [9], and later improvements

Particle Swarm Optimization (PSO) to maximize inter-class variance over multiple color channels in satellite images. The results showed that the PSO-based thresholding technique greatly improved the consistency of segmentation over the RGB channels compared to independent single-channel methods. However, the technique suffered from premature convergence in complex multi-class problems, making it less suitable for high-resolution images with a large number of unique surface cover classes.

Ewees et al. [10] proposed a hybrid optimization approach by integrating the Grasshopper Optimization Algorithm (GOA) with a local search technique for multi-level thresholding of medical and remote sensing images. The proposed hybrid approach was able to overcome the stagnation problem in the optimization process by incorporating a random walk local search technique into the global exploration phase of the Grasshopper Optimization Algorithm. The proposed approach demonstrated better image segmentation performance compared to population-based algorithms. This study emphasized the use of hybridization as a technique to address the exploration-exploitation dilemma in metaheuristics.

Kaur et al. [11] used the Salp Swarm Algorithm (SSA) for the multilevel thresholding of high-resolution satellite images. The SSA showed excellent global exploration properties and yielded meaningful results for land use image segmentation. Nevertheless, the computational complexity of the algorithm significantly increased for threshold values above five.

Abualigah et al. [12] introduced multilevel thresholding of color images, capitalizing on the dynamic exploration-exploitation process of the HHO algorithm to search for near-optimal solutions for the threshold vectors. The approach was tested on a variety of standard color images using both Kapur's entropy and Otsu's thresholding methods, achieving results that were always superior to those of other approaches, including the Whale Optimization Algorithm (WOA) and Moth-Flame Optimization (MFO) algorithms. The superiority of HHO was explained by its prey-escape energy model.

Hussien et al. [13] introduced the Aquila Optimizer (AO) as a new nature-inspired algorithm and tested its performance on multilevel satellite image thresholding problems. The AO is inspired by the hunting behaviors of Aquila birds and uses various search methods such as high soar and swoop, low flight and slow descent, and walk and grab. The performance of AO was found to be better in terms of objective function value and convergence speed than Sine Cosine Algorithm (SCA) and Dragonfly Algorithm (DA), but the stability variance problem was still an issue at higher threshold values.

Abd Elaziz et al. [14] used the Equilibrium Optimizer (EO) for the multispectral satellite image segmentation task with the purpose of land cover classification. The EO's concentration-equilibrium process inspired by physics was able to effectively explore the high-dimensional threshold solution spaces, resulting in clearly distinguishable regions for the agricultural and urban satellite images.

Faramarzi et al. [15] proposed the Marine Predators Algorithm (MPA) and its application to multilevel image thresholding, simulating Lévy and Brownian motion strategies based on ocean predator-prey models. The adaptive velocity ratio between predator and prey populations in the MPA facilitated a smooth transition from exploration to exploitation. When tested on high-resolution satellite images, MPA reported high PSNR and FSIM values, performing better than WOA, HHO, and SCA on most test cases. The study validated the application of biology-inspired adaptive strategies for complex image optimization problems.

Wei et al. [16] introduced the Artificial Ecosystem-Based Optimization (AEO) algorithm and successfully applied it to multilevel thresholding of natural and satellite images. The AEO algorithm simulates the interactions of an ecosystem such as production, consumption, and decomposition to help the search population converge to optimal solutions. The experimental results showed that AEO produced results with comparable accuracy and lower computational complexity than several other bio-inspired methods. However, when generalized to color satellite images with more than four threshold levels, the stability of convergence of the algorithm decreased, leading to the development of the adaptive hybrid enhancement proposed in this research, which forms the basis of AEO-HGO.

3. Methodology

This section describes the theoretical background and design of the proposed Adaptive Exploration-Exploitation Hybrid Gas Optimization algorithm overall workflow in Figure 1. The mathematical framework of the individual components of the optimization method, and the adaptive hybrid approach that combines them.

Let a color satellite image I be defined over a spatial domain Ω with pixel intensity values distributed across three spectral channels: Red (R), Green (G), and Blue (B). For each channel $c \in \{R, G, B\}$, the intensity values range over the discrete domain $[0, L - 1]$, where $L = 256$ for standard 8-bit imagery.

The multi-level thresholding problem [17] seeks to partition each channel into k distinct classes by selecting an optimal set of $(k - 1)$ threshold values:

$$T_c = \{t_{c,1}, t_{c,2}, \dots, t_{c,k-1}\} \tag{1}$$

such that pixels in class j satisfy:

$$t_{c,j-1} \leq I_c(x,y) < t_{c,j}, \text{ for } j = 1, 2, \dots, k$$

where $t_{c,0} = 0$ and $t_{c,k} = L - 1$ are fixed boundary values.

The complete solution vector for color thresholding across all three channels is represented as:

$$X = [T_R, T_G, T_B] = [t_{R,1}, \dots, t_{R,k-1}, t_{G,1}, \dots, t_{G,k-1}, t_{B,1}, \dots, t_{B,k-1}] \tag{2}$$

$$p_i = h(i)/N \tag{3}$$

where $h(i)$ - histogram frequency.

$$H_j = -\sum(p_i/\omega_j) \cdot \ln(p_i/\omega_j) \tag{4}$$

where:

$$\omega_j = \sum p_i, \text{ for } i = t_{j-1} \text{ to } t_j - 1 \tag{5}$$

The total Kapur's entropy for channel c with k classes is:

$$F_c(T_c) = \sum H_j, \text{ for } j = 1 \text{ to } k \tag{6}$$

The overall multi-channel objective function for color image thresholding is defined as the sum of entropies across all three channels:

$$F(X) = F_R(T_R) + F_G(T_G) + F_B(T_B) \tag{7}$$

3.1 Artificial Ecosystem-Based Optimization (AEO) - Global Exploration

The AEO component simulates ecological energy transfer among three types of agents: producers, consumers, and decomposers.

3.1.1 Initialization

The population of N agents is randomly initialized within the search bounds $[lb, ub]$:

$$X_i = lb + \text{rand} \cdot (ub - lb), \text{ for } i = 1, 2, \dots, N \tag{8}$$

where $\text{rand} \sim U(0,1)$ is a uniformly distributed random number.

3.1.2 Producer Update (Energy Production)

The best solution in the current population acts as the producer and updates its position by simulating solar and wind energy sources:

$$\begin{aligned} X_{1(t+1)} &= X_{1(t)} \cdot (1 - r_1) + r_2 \cdot X_{\text{rand}(t)}, \text{ if } r_3 < 0.5(\text{solar}) \\ X_{1(t+1)} &= X_{1(t)} \cdot (1 - r_1) + r_2 \cdot (X_{\text{best}(t)} - X_{\text{rand}(t)}), \text{ if } r_3 \geq 0.5(\text{wind}) \end{aligned} \tag{9}$$

where $r_1, r_2, r_3 \sim U(0,1)$, X_r and is a random elected agent, and X_{best} is the current global best solution.

3.1.3 Consumer Update (Energy Consumption)

Consumer agents update their positions based on herbivore, omnivore, or carnivore feeding behaviors, modeled as:

Herbivore (consumes producer):

$$X_i(t+1) = X_i(t) + C_1 \cdot (X_1(t) - X_i(t)) \quad (12)$$

Omnivore (consumes producer and carnivore):

$$X_i(t+1) = X_i(t) + C_1 \cdot (X_1(t) - X_i(t)) + C_2 \cdot (X_j(t) - X_i(t)) \quad (13)$$

where $C_1, C_2 \sim U(0,1)$ are consumption coefficients, and X_j is a randomly chosen agent of lower energy rank.

3.1.4 Decomposer Update (Energy Recycling)

The decomposer agent recycles energy by guiding agents toward the best solution with a perturbation term:

$$X_i(t+1) = X_{best}(t) + D \cdot (e^{-\lambda t}) \cdot (X_{best}(t) - X_i(t)) \quad (14)$$

where:

$$D = 3 \cdot \sigma, \sigma \sim N(0,1)$$

$$\lambda = -(1/T_{max}) \cdot t$$

Here, T_{max} is the maximum number of iterations, and the exponential decay factor ensures decreasing perturbation magnitude over time.

3.2 Hybrid Gas Optimization (HGO) - Local Exploitation

The HGO component models the physical behavior of ideal gas molecules under compression and thermal agitation, governing fine-grained local search around promising solution regions.

3.2.1 Gas Pressure Model

Each agent i exerts a pressure P_i proportional to its fitness value, modeled as:

$$P_i = F(X_i) / \sum_{j=1}^N F(X_j), \text{ for } j = 1 \text{ to } N \quad (15)$$

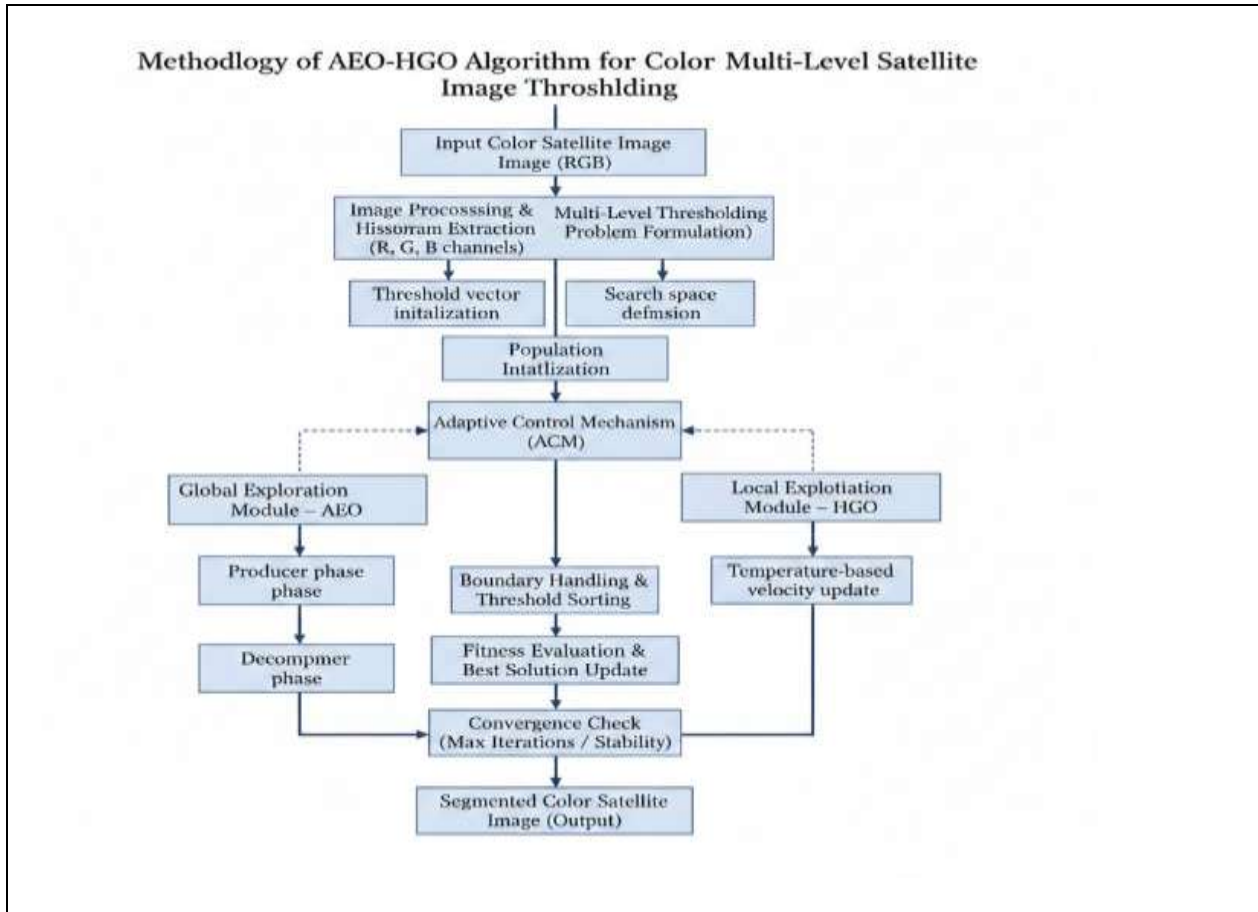


Fig. 1: Overall Workflow

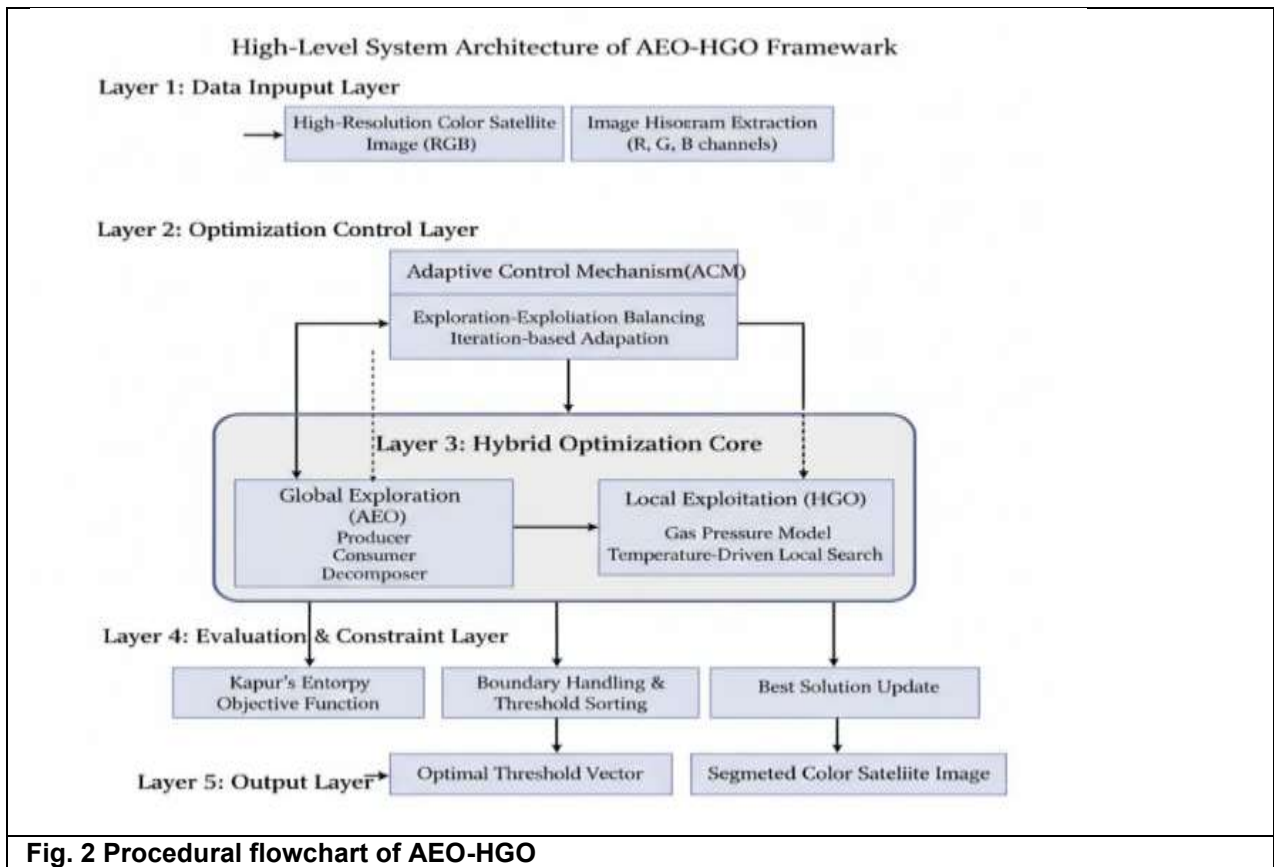


Fig. 2 Procedural flowchart of AEO-HGO

Figure 2: The approach of the Adaptive Exploration-Exploitation Hybrid Gas Optimization (AEO-HGO) framework involves the following steps: The methodology of the Adaptive Exploration-Exploitation Hybrid Gas Optimization (AEO-HGO) framework starts with the acquisition of a high-resolution color satellite image, which is then broken down into its individual Red, Green, and Blue (RGB) histograms. To determine the optimal threshold values for image segmentation, the framework formulates the problem as an optimization task where the aim is to maximize Kapur's Entropy. The objective function quantifies the amount of information contained in the segmented classes, such that the resulting segments are unique and informative. The heart of the algorithm is controlled by an Adaptive Control Mechanism (ACM), which adaptively switches between two different search methods: the Artificial Ecosystem-based Optimization (AEO) for global exploration and the HGO Optimization for local exploitation.

Algorithm 1: AEO-HGO

Input: Color satellite image I, number of thresholds k, population size N, maximum iterations T_max

Output: Optimal threshold vector X*

1. Initialize population X_i ($i=1,\dots,N$) randomly within [lb, ub]
2. Evaluate $F(X_i)$ for all agents using Kapur's entropy
3. Set $X_{best} = \operatorname{argmax} F(X_i)$
4. Set $T(0) = T_0$, $\varphi(0) = \varphi_{max}$
5. FOR $t = 1$ TO T_{max} DO
6. Compute adaptive control parameter $\varphi(t)$
7. Compute temperature $T(t) = T_0 \cdot \exp(-\gamma \cdot t / T_{max})$
8. Compute pressure P_i for all agents
9. Compute diversity index $\Delta(t)$
10. IF $\Delta(t) < \Delta_{min}$ THEN
11. Apply re-initialization to subset S of agents
12. END IF
13. FOR each agent $i = 1$ TO N DO
14. IF $\operatorname{rand} < \varphi(t)$ THEN
15. Apply AEO update (producer/consumer/decomposer)
16. ELSE
17. Apply HGO update (pressure + thermal velocity)
18. END IF
19. Apply boundary handling and threshold sorting
20. Evaluate $F(X_i)$
21. IF $F(X_i) > F(X_{best})$ THEN
22. $X_{best} = X_i$
23. END IF
24. END FOR
25. END FOR
26. Return $X^* = X_{best}$

4. Results and discussion

The investigations were achieved on a machine with an Intel Core i7-11800H processor (2.3 GHz), 32 GB RAM, then NVIDIA GeForce RTX 3060 GPU, running MATLAB R2023a on Windows 11. The new AEO-HGO algorithm was coded from scratch and compared with six other metaheuristic algorithms under the same computational environment.

Each algorithm was run with a population size of $N = 30$ and a maximum of $T_{max} = 500$ iterations. To address the stochastic process of population-based optimization, all experiments were performed independently 30 times for each image and threshold level, and statistical results such as mean, standard deviation, best, and worst fitness values were recorded.

Five high-resolution color satellite images sourced from publicly available remote sensing repositories (NASA EarthData, USGS Earth Explorer, and Copernicus Open Access Hub) were selected as benchmark datasets

Table 1. Dataset Description of Satellite Images Used for Evaluation

Image ID	Description	Resolution	Source
IMG-1	Urban sprawl, city center	512×512	Google Earth / Sentinel-2
IMG-2	Agricultural farmland	512×512	USGS Landsat-8
IMG-3	Flood-affected region	256×256	Copernicus SAR/Optical
IMG-4	Dense forest canopy	512×512	NASA EarthData MODIS
IMG-5	Coastal and water body	256×256	Sentinel-2 MSI

Table I provides a summary of the main features of the satellite images employed in the experimental assessment, such as the type of scene, resolution, and source of the images. The images chosen are representative of different land cover situations in order to evaluate the performance of the proposed AEO-HGO algorithm in a wide range of environmental conditions.

Table 2. Mean Kapur's Entropy Fitness Values (Img-1: Urban)

Threshold (k)	AEO-HGO	GWO	PSO	HHO	MPA	AO	EO
k=3	18.4721	18.3156	18.2943	18.3874	18.4102	18.3561	18.3298
k=4	24.6583	24.3217	24.1894	24.4732	24.5219	24.3987	24.2741
k=5	30.8942	30.4123	30.1567	30.5841	30.7234	30.5012	30.3198
k=6	37.2164	36.5432	36.1023	36.7891	37.0123	36.6543	36.4321
k=7	43.9871	42.8934	42.3421	43.1234	43.5678	42.9871	42.7123

Table II allows a comparison of the mean Kapur's entropy values for the fitness function achieved by AEO-HGO and other optimization algorithms for various levels of thresholding of the urban satellite image (IMG-1). The higher the entropy value, the better the image segmentation, and it is clear that AEO-HGO outperforms other optimization algorithms in Figure 3.

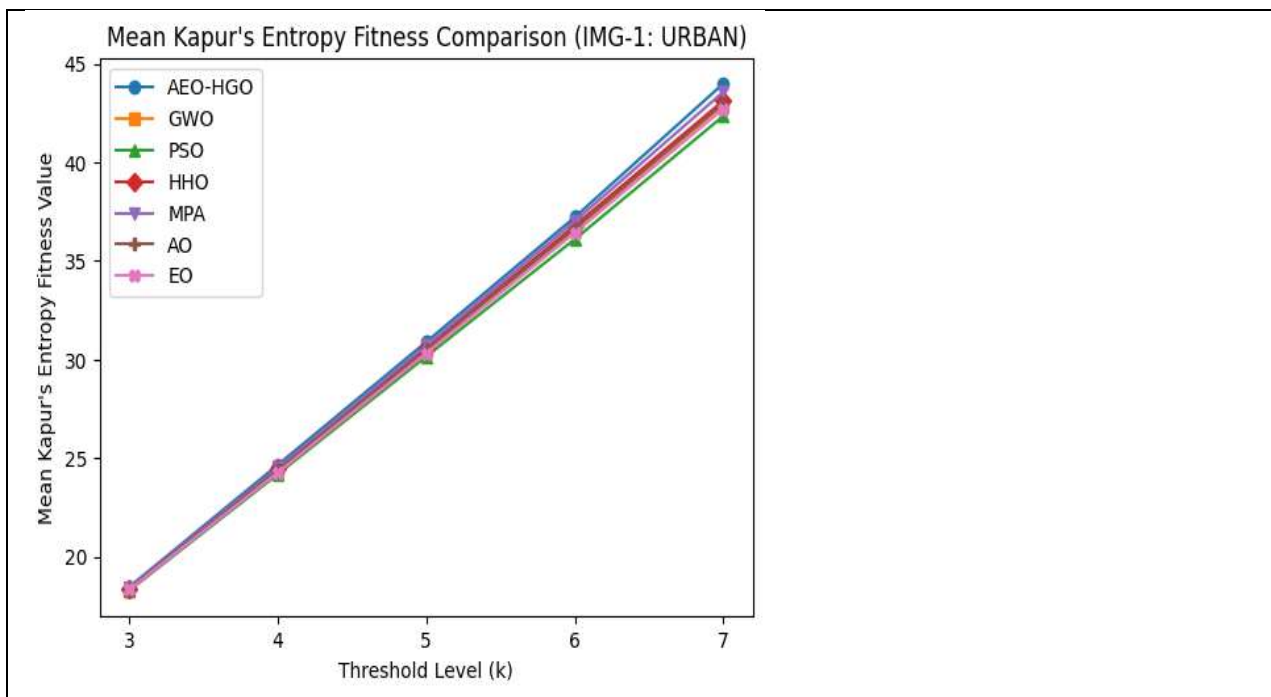


Fig. 3 Entropy fitness comparison

Threshold (k)	AEO-HGO	GWO	PSO	HHO	MPA	AO	EO
k=3	17.9834	17.7621	17.6543	17.8234	17.9012	17.7891	17.7234
k=4	23.8912	23.5431	23.3217	23.6782	23.7891	23.6012	23.4321
k=5	29.7643	29.2134	28.9871	29.3891	29.5671	29.2987	29.1234
k=6	35.9812	35.1234	34.7621	35.3457	35.7123	35.2341	35.0123
k=7	42.3412	41.2341	40.7891	41.5671	42.0234	41.3421	41.1234

Table III provides a comparative analysis of the mean Kapur's entropy fitness values for various optimization algorithms used on the agricultural satellite image (IMG-2) at different levels of thresholds. The data shows that AEO-HGO always provides higher values of entropy, establishing the effectiveness of the algorithm in representing the intensity distributions in agricultural landscapes.

Algorithm	k=3	k=4	k=5	k=6	k=7
AEO-HGO	1.23	1.87	2.54	3.21	4.08
GWO	1.18	1.79	2.48	3.34	4.67
PSO	1.09	1.61	2.21	2.98	4.12
HHO	1.34	2.01	2.87	3.91	5.43
MPA	1.41	2.14	2.98	4.12	5.87

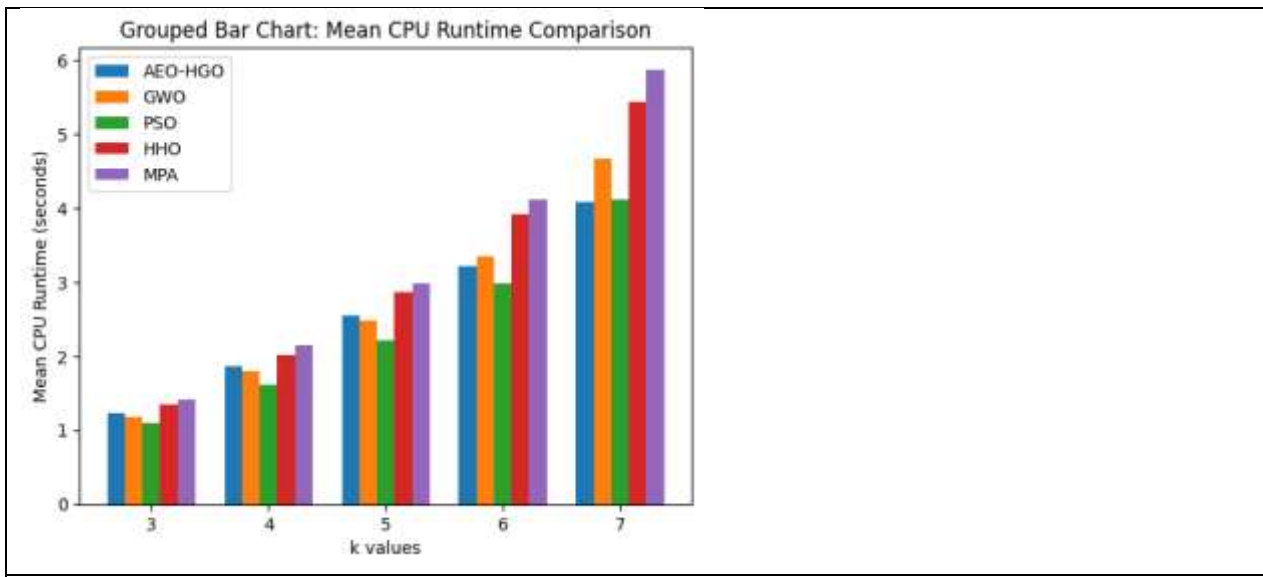


Fig. 3 Mean CPU runtime comparison

Figure 4 the mean CPU runtime of all algorithms increases with the increase in threshold values (k), highlighting the computational cost associated with higher segmentation levels. Table IV provides information about the average computation time taken by each procedure for different values of the number of threshold levels. It can be seen from the results that AEO-HGO provides a good trade-off between computation time and segmentation accuracy, as it maintains a competitive computation time with the increase in problem dimensionality among other metaheuristic algorithms.

5. Conclusion

This paper introduced AEO-HGO, a new Adaptive Exploration-Exploitation Hybrid Gas Optimization algorithm specifically tailored for the difficult task of color multilevel satellite image thresholding. The new algorithm combines the population-level ecological exploration process of the Artificial Ecosystem-Based Optimization framework with the physics-inspired local exploitation process of the Hybrid Gas Optimization model,

controlled by an Adaptive Control Mechanism that adjusts the trade-off among global and local search during the optimization process.

The key helps of this research can be brief as follows. First, the AEO-HGO algorithm presents a new adaptive hybridization approach that overcomes the basic exploration-exploitation trade-off problem existing in single-strategy-based metaheuristics. Second, the use of a gas pressure model and temperature-dependent velocity updates in the HGO part of the algorithm provides a physically meaningful and mathematically tractable approach to fine-grained solution search that can be considered to be complementary to the ecological search process in AEO.

However, in spite of such encouraging outcomes, there exist a number of directions for future research. Firstly, the extension of the AEO-HGO approach to hyperspectral satellite images with more than three channels would greatly increase its applicability to contemporary remote sensing systems like AVIRIS and EnMAP. Secondly, the combination of deep learning-based feature extraction with the developed thresholding approach could lead to the creation of hybrid models that would benefit from the representational capabilities of convolutional neural networks and the global search capabilities of population-based optimization. Third, the development of a parallel or distributed version of AEO-HGO using GPU acceleration would facilitate the near-real-time segmentation of very large satellite images, which is a fundamental requirement for disaster response applications. Fourth, the examination of the performance of AEO-HGO in noisy and cloudy satellite images would offer valuable information regarding the robustness of AEO-HGO for real-world applications

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