NEÜ PRESS

Necmettin Erbakan Üniversitesi
Fen ve Mühendislik Bilimleri Dergisi
Journal of Science and Engineering (NEJSE)
DOI: 10.47112/neufmbd.2023.21

Cilt: 5 Sayı:2 Yıl: 2023 | Araştırma Makelesi / Research Article | E-ISSN: 2667- 7989

Çok Seviyeli Görüntü Eşikleme Problemini Çözmek İçin Harmoni Aramalı Yeni Bir Hibrit Gri Kurt Optimizasyon Algoritması

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Makale Bilgileri

Makale Geçmişi
Geliş: 03.09.2023
Kabul: 15.10.2023
Yayın: 31.12.2023

Anahtar Kelimeler:
Gri kurt optimizasyon,
Harmoni arama,
Kapur,
Çok seviyeli görüntü eşikleme,
Otsu.

ÖZ

Çok seviyeli görüntü eşikleme, görüntüyü ileri düzeyde anlamlı özelliklere ayırmak için kullanılan önemli bir görüntü işleme tekniğidir. Bu teknik, metasezgisel optimizasyon algoritmaları ile birlikte kullanılarak hesaplama süresi açısından başarılı sonuçlar elde edilebilmektedir. Bu çalışmada, çok seviyeli görüntü eşikleme problemini çözmek için GWO-HS olarak isimlendirilen hibrit bir algoritma önerilmiştir. Önerilen algoritma gri kurt optimizasyon (GWO) ve harmoni arama (HS) algoritmaları hibritlenerek elde edilmiştir. GWO-HS algoritmasının performansı beş diğer algoritmanın performansları ile karşılaştırılmıştır. Karşılaştırmalarda Otsu ve Kapur entropi tabanlı eşikleme yöntemleri kullanılmıştır. Deneylerde, görüntü işleme çalışmalarında iyi bilinen ve yaygın olarak kullanılan altı görüntü tercih edilmiştir. Her bir görüntü üzerinde 2'den 10'a kadar değişen seviyeler için eşikleme işlemi uygulanmıştır. Sonuçlar, önerilen GWO-HS algoritmasının, diğer algoritmalara kıyasla özellikle yüksek eşik seviyeleri için daha üstün bir performansa sahip olduğunu göstermiştir.

A Novel Hybrid Gray Wolf Optimization Algorithm with Harmony Search to Solve Multi-Level Image Thresholding Problem

Article Info

Article History
Received: 03.09.2023
Accepted: 15.10.2023
Published: 31.12.2023

Keywords:
Grey wolf optimization,
Harmony search,
Kapur,
Multi-level image thresholding,
Otsu.

ABSTRACT

Multi-level image thresholding is an important image processing technique used to separate an image into advanced meaningful features. By using this technique together with metaheuristic optimization algorithms, successful results can be achieved in terms of computational time. In this study, a hybrid algorithm called GWO-HS was proposed to solve the multi-level image thresholding problem. The proposed algorithm was obtained by hybridizing the Gray Wolf Optimization (GWO) and Harmony Search (HS) algorithms. The performance of the GWO-HS algorithm was compared with the performances of five other algorithms. Otsu and Kapur entropy-based thresholding methods were used in the comparisons. In the experiments, six images, which are well known and widely used in image processing studies, were preferred. Thresholding was applied for threshold levels ranging from 2 to 10 on each image. The results showed that the proposed GWO-HS algorithm has superior performance compared to other algorithms, especially for high threshold levels.

Atıf/Citation Ünlü, A. & İlhan, İ. (2023). A novel hybrid gray wolf optimization algorithm with harmony search to solve multi-level image thresholding problem, *Necmettin Erbakan University Journal of Science and Engineering*, 5(2), 230-245. https://doi.org/10.47112/neufmbd.2023.21

INTRODUCTION

Multi-level image thresholding is a classification process that separates image data according to multiple thresholds. In this process, the pixel values in the image are compared to predetermined threshold values and they are updated according to the relevant threshold value. Thus, it is aimed to separate and characterize the objects in the image. Image thresholding is a commonly preferred methods in the fields of image processing and computer vision. It is frequently used in various applications such as character recognition [1], target identification [2], multiple objects tracking on video [3] and medical imaging [4].

Image thresholding methods are commonly applied on grayscale images. Two-level or multi-level thresholding is performed according to the threshold values obtained from the histogram of the grayscale image. Thresholding methods based on histogram information are simple and effective techniques. The most common of these methods are Otsu and Kapur entropy-based thresholding methods. While Otsu thresholding method uses variance information, Kapur entropy-based thresholding method uses entropy information. These methods produce fast results for a single threshold value. However, as the number of thresholds to be obtained from the image increases, the computation time increases exponentially. It is necessary to use optimization algorithms to obtain the optimum threshold value and reduce the computation time.

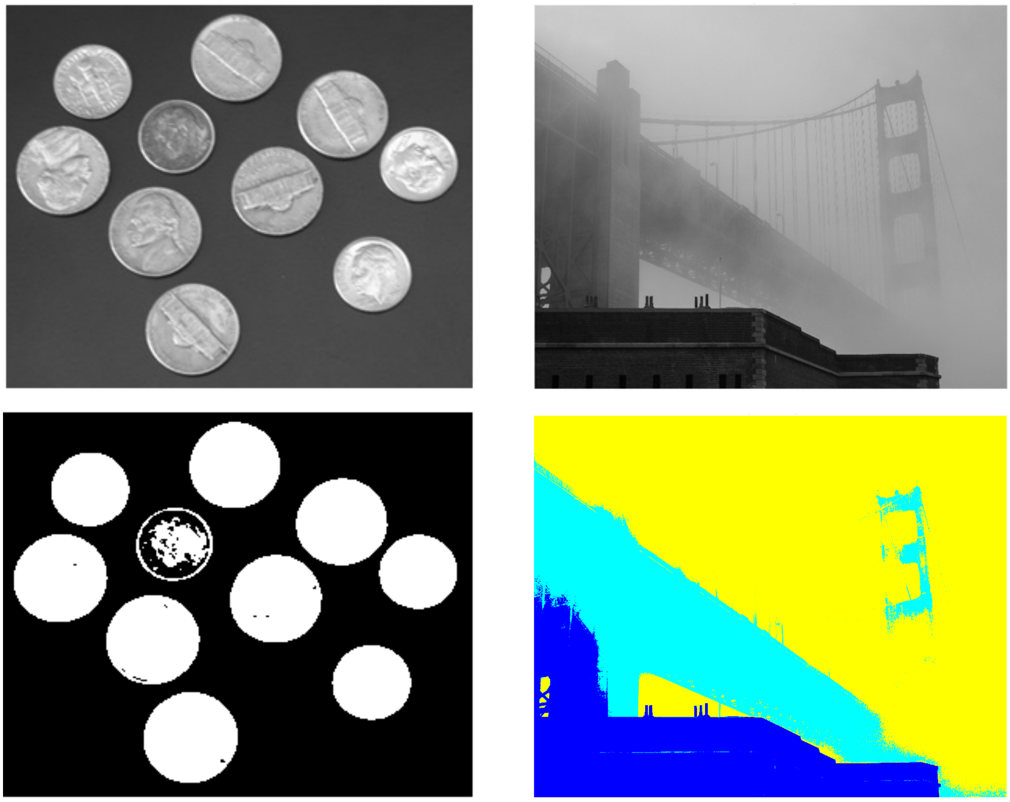
Metaheuristic algorithms are nature-inspired algorithms that minimize or maximize the given objective function in optimization problems. These algorithms can solve many different types and properties of problems such as continuous, discrete and binary optimization problems [5-7]. These algorithms can even be successfully applied to clustering problems [8]. The multi-level image thresholding problem is considered as a continuous optimization problem and metaheuristic algorithms are widely used to solve this problem. Some of the algorithms used in these studies are genetic algorithm (GA) [9], improved bat algorithm (IBA) [10], cuckoo search (CS) algorithm [11], firefly search (FS) algorithm [12], artificial bee colony (ABC) algorithm [13], particle swarm optimization (PSO) algorithm [14], differential evolution algorithm (DE) [15].

In this paper, a hybrid algorithm called GWO-HS was proposed to solve the multi-level image thresholding problem. The proposed algorithm was obtained by hybridizing grey wolf optimization (GWO) and harmony search (HS) algorithms. The performance of GWO-HS algorithm was compared with the performance of basic algorithms such as genetic (GA), grey wolf optimization (GWO), harmony search (HS), particle swarm optimization (PSO) and simulated annealing (SA). Otsu and Kapur entropy-based thresholding methods were used in the comparisons. “Barbara”, “Living room”, “Boats”, “Goldhill”, “Lake” and “Aerial” images, which are well known and widely used in image processing studies, were used in the experiments. Thresholding was applied for threshold levels (numbers) ranging from 2 to 10 on each image.

MULTI-LEVEL IMAGE THRESHOLDING

Thresholding methods are divided into two groups: single-level and multi-level thresholding. In single-level thresholding, the image is divided into two different regions. For this, firstly, an appropriate T threshold value is determined. Then, the pixels with gray intensity values greater than this value are classified as object (foreground) pixels. Other pixels with gray density values smaller than the T threshold value are classified as background pixels. After this binary transformation process, a grayscale image is converted into a binary image [16]. In multi-level thresholding, the image is divided into several different regions. In this method, more than one threshold value is determined for a given grayscale image. Then, the image is divided into specific brightness regions corresponding to a background and several objects (foreground). The multi-level thresholding method works very well on images containing colored objects and complex backgrounds, where the single-level thresholding method cannot produce satisfactory results [17].

An example of single-level and multi-level thresholding methods is presented in Fig. 1. Fig. 1a shows an example image and its thresholded version according to the threshold value of 126. Fig. 1b shows an example image and its thresholded version according to threshold values of 80 and 147.



(a) (b)

Figure 1. *(a) Single-level thresholding (b) multi-level thresholding.*

Various methods were proposed for determining threshold values in multi-level image thresholding. The most common of these methods are Otsu and Kapur entropy-based methods, which are also used in this study and described in detail below.

Otsu Thresholding Method

Otsu thresholding method is one of the most widely used thresholding algorithms based on maximizing the variance between classes. Proposed in 1979 by Nobuyuki Otsu, it is a threshold detection method that can be applied to greyscale images [18].

The probabilities of pixels at level i of an image I with L gray levels are denoted by p_i. The sum of these probabilities is equal to 1. So $p_i \geq 0$ and $p_0 + p_1 + \ldots + p_{L-1} = 1$. ω_0 is the sum of the probabilities of the pixels up to the threshold of the image. μ_T is the value of the average gray level of the image. The average value for each class is denoted by μ_i and the mathematical expressions for the objective function are given in Equations 1-5.

$$f(t) = \sum_{i=0}^{n} \sigma_i \tag{1}$$

$$\omega_0 = \sum_{i=0}^{t_0-1} p_i \ , \omega_1 = \sum_{i=t_0}^{t_1-1} p_i \ , \ldots \ \omega_k = \sum_{i=t_{k-1}}^{L-1} p_i \tag{2}$$

$$\sigma_0 = \omega_0 \ (\mu_0 - \mu_T)^2 \, , \sigma_1 = \omega_1 \ (\mu_1 - \mu_T)^2 , \ldots , \sigma_1 = \omega_n \ (\mu_n - \mu_T)^2 \tag{3}$$

$$\mu_0 = \sum_{i=0}^{t_1-1} \frac{ip_i}{\omega_i}\ \mu_1\ ,\quad \mu_1 = \sum_{i=t_1}^{t_2-1} \frac{ip_i}{\omega_i}\ , \mu_2 = \sum_{i=t_3}^{t_3-1} \frac{ip_i}{\omega_i}\ \mu_1\ ,\quad \mu_m = \sum_{i=t_m}^{L-1} \frac{ip_i}{\omega_i} \tag{4}$$

$$(t)^* = argmax\left(\sum_{i=0}^{m} \sigma_i\right) \tag{5}$$

Kapur Entropy-Based Thresholding Method

Kapur's entropy-based function was initially proposed in 1985 for segmentation by maximizing the entropy of a grey level image histogram [19]. This method uses entropy as an objective function to find the optimum threshold value for image segmentation processes. In single-level thresholding, the threshold value is determined to divide the image into foreground and background regions. In Kapur's entropy method, the entropy of each region is calculated individually to find the optimum threshold and the value with the maximum entropy is determined as the threshold value [20].

Considering that any image with N pixel values has L gray levels 0, 1, 2, ..., L-1, the probabilities of the gray level values in the image are Pi and h(i) indicates the number of pixels with gray level i in the image. Considering that there are k threshold values in the segmentation process, the mathematical expressions of the objective function are given in Equations 6-8.

$$P_i = h(i)/N \tag{6}$$

$$f(t) = \arg\max\left(\sum_{i=0}^{1} H_i)\right) \tag{7}$$

$$\begin{aligned}
\omega_0 &= \sum_{i=0}^{t_0-1} Pi & H_0 &= -\sum_{i=0}^{t_0-1} \frac{P_i}{\omega_0} \ln \frac{P_i}{\omega_0} \\
\omega_1 &= \sum_{i=t_0}^{t_1-1} Pi & H_0 &= -\sum_{i=t_0}^{t_1-1} \frac{P_i}{\omega_1} \ln \frac{P_i}{\omega_1} \\
\omega_k &= \sum_{i=t_{k-1}}^{L-1} Pi & H_0 &= -\sum_{i=t_{k-1}}^{L-1} \frac{P_i}{\omega_k} \ln \frac{P_i}{\omega_k}
\end{aligned} \tag{8}$$

MATERIALS AND METHODS

In this study, a hybrid algorithm was developed to solve the multi-level image thresholding problem. This algorithm was named as GWO-HS. The GWO-HS was obtained by hybridizing the GWO and HS algorithms. In this section, the GWO and HS algorithms are first explained. Then, the GWO-HS algorithm is described in detail.

Grey Wolf Optimization Algorithm

The grey wolf optimization (GWO) algorithm is a population-based metaheuristic algorithm inspired by the social leadership and hunting behavior of wolves. It was proposed by Mirjali et al. [21]. The social hierarchy structure of gray wolves is classified as alpha, beta, delta and omega. Alpha male and female wolves are at the top of the hierarchy and lead the pack. They are followed by the beta wolf, who supports the decisions of the alpha wolf and helps maintain discipline within the pack. The delta wolf is below the beta wolf in the hierarchy. They are usually strong but lack the skills or confidence to lead. There are the omega wolves at the bottom of the hierarchy. Omega wolves have no power.

In the GWO algorithm, the search process starts by generating a random population of gray wolves (candidate solutions). Over iterations, alpha, beta and delta wolves estimate the likely location of the prey. Each candidate solution updates its distance from the prey using Equation 13.

$$A = 2.a.r_1 - a \tag{9}$$

$$C = 2.r_2 \tag{10}$$

$$D_\alpha = |C_1\, X_\alpha - X|,\ D_\beta = |C_2\, X_\beta - X|,\ D_\delta = |C_3\, X_\delta - X| \tag{11}$$

$$X_1 = X_\alpha - A_1.D_\alpha,\ X_2 = X_\beta - A_2.D_\beta,\ X_3 = X_\delta - A_3.D_\delta \tag{12}$$

$$X(t+1) = \frac{X_1 + X_2 + X_3}{3} \tag{13}$$

Here, t represents the current iteration. A and C are coefficients. r1 and r2 are randomly generated values in the range [0, 1]. X indicates the position of a gray wolf. Xα, Xβ and Xδ represent the positions of alpha, beta, and delta wolves, respectively. In the GWO algorithm, to increase the importance of the discovery, the parameter a is decreased from 2 to 0. Candidate solutions tend to move away from the prey when |A|>1 and closer to it when |A|<1. Finally, the GWO algorithm is terminated by satisfying the stopping criterion. Fig. 2 shows the pseudocode of the GWO algorithm.

```
Initialize parameters IN and PS
IN: Number of Iterations, PS: Population Size
Initialize the population of gray wolf, Xi (i = 1, 2, 3, …., PS)
Initialize a, A and C
Calculate the fitness values of all search agents
Determine Xα, Xβ and Xδ
Xα: Best search agent, Xβ: Second best search agent, Xδ: Third best search agent
t = 0
while t < IN
    foreach Xi in X
        Update the position of the current search agent with Equations 11-13
    end foreach
    Update a, A and C values
    Calculate the fitness values of all search agents
    Update Xα, Xβ and Xδ
    t = t + 1
end while
Return Xα
```

Figure 2. *Pseudocode of the GWO algorithm*

Harmony Search Algorithm

Musical performances seek the best state (fantastic harmony) determined by the aesthetic prediction, while optimization algorithms aim to find the best state (global optimum) determined by the objective function. The aesthetic prediction is determined by the set of sounds played by various instruments. The value of objective function is determined by the set of values produced by the variables. For a better aesthetic prediction, sounds can be improved by practicing. For a better the value of objective function, the variable values can be iteratively improved.

The new algorithm that mimics the way musicians try different notes to create a perfect harmony is called the harmony search (HS) algorithm. This algorithm was first proposed in 2001 and has been successfully used to solve various engineering problems [22]. Fig. 3 shows the pseudocode of the HS algorithm.

```
Initialize parameters IN, HMS, HMCR, PAR, BW and BWF
IN: Number of Iterations, HMS: Harmonic Memory Size, HMCR: Harmony Memory
Consideration Ratio, PAR: Pitch Adjustment Ratio, BW: Bandwidth, BWF: Bandwidth Factor
Generate HM randomly, HM = {X^1, X^2, …X^HMS}
Determine the worst harmony in HM, X^worst ∈ {X^1, X^2, …X^HMS}
t = 0
while (t < IN)
    foreach i ∈ [1, D]                                  // D: Number of notes
        if rand(0,1) < HMCR
            X_i^new = X_i^R ∈ {X_i^1, X_i^2, …, X_i^HMS}    // Consideration of harmony memory
            if rand(0,1) < PAR
                X_i^new = X_i^new ± rand(0,1). BW(i)    // Tone adjustment
            end if
        else
            X_i^new = X_i^L ± rand(0,1). (X_i^U − X_i^L)   // Randomization
        end if
    end foreach
    if X^new.IsBetter(X^worst)
        X^worst = X^new
    end if
    BW = BW * BWF
    t = t + 1
end while
Return X^best ∈ {X^1, X^2, …X^HMS}
```

Figure 3. *Pseudocode of the HS algorithm*

Proposed Hybrid GWO-HS Algorithm

In this study, the GWO and HS algorithms were hybridized to solve the multi-level image thresholding problem and the GWO-HS algorithm was developed. The pseudocode of the GWO-HS algorithm is given in Fig. 4. As can be seen from the figure, at the beginning of the algorithm, iteration number (IN), population size (PS) and bandwidth (BW) values are determined. Then, the gray wolf population Xi is randomly generated. Xi is represented by a matrix with element values between 0 and 255. The number of rows of this matrix is equal to PS and the number of columns is equal to the number of thresholds to be detected in the image. After the generation of the population, the values of a, A and C are determined and the bandwidth factor BWF is calculated by the formula 〖((2)⁄(BW))〗^(1⁄((IN-1))). The fitness values of all search agents (gray wolves) are calculated. The three gray wolves with the best fitness values (Xα, Xβ and Xδ) are identified. The section from line 7 to line 22 represents the iteration process. When these lines are analyzed, it is seen that the section except for lines 14-20 is the same as the iteration process of the GWO. The section between lines 14-20 represents the tone adjustment phase of the HS. Unlike the tone tuning phase in the HS, in the GWO-HS algorithm, the tone tuning process is applied only to alpha, beta and delta wolves. Thus, about these wolves, better wolves in terms of fitness value are tried to be detected.

The tone adjustment process in the GWO-HS algorithm is used for the local search process. At the end of each iteration, the bandwidth value is multiplied by the bandwidth factor and reduced. Thus, at the beginning of the iterations, neighboring solutions in more remote areas are searched, while at the end of the iterations, neighboring solutions in closer areas are searched. The effect of the tone adjustment process is better seen as the threshold number increases. For low threshold numbers, the GWO and GWO-HS algorithms achieve similar results. However, as the threshold number increases, the GWO-HS algorithm achieves better results than the GWO and other algorithms. This can be clearly seen from the tables shared in the next section.

```
Initialize parameters IN, PS and BW
IN: Number of Iterations, PS: Population Size, BW: Bandwidth
Initialize the population of gray wolf, X_i (i = 1, 2, 3, …., PS)
Initialize a, A, C and BWF
 BWF (Bandwidth Factor) = (2/BW)^(1/(IN−1))
Calculate the fitness values of all search agents
Determine X_α, X_β and X_δ
X_α: Best search agent, X_β: Second best search agent, X_δ: Third best search agent
 t = 0
 while t < IN
     foreach X_i in X
         Update the position of the current search agent with Equations 11-13
     end foreach
     Update a, A and C values
     Calculate the fitness values of all search agents
     Update X_α, X_β and X_δ
     for k = 1 to 10
         X^new_α,β,δ = X^new_α,β,δ ± rand(0, 1). BW
         if X^new_α,β,δ.IsBetter(X_α,β,δ)
             X_α,β,δ = X^new_α,β,δ
         end if
     end for
     BW = BW * BWF
     t = t + 1
 end while
 Return X_α
```

Figure 4. *Pseudocode of the GWO-HS algorithm*

RESULTS

In this study, the performance of the proposed GWO-HS algorithm was compared with the performances of the GA, GWO, HS, PSO and SA algorithms using the Otsu and Kapur entropy-based thresholding methods. In the experiments, “Barbara”, “Living room”, “Boats”, “Goldhill”, “Lake” and “Aerial” images, which are widely preferred in image processing studies, were used. Among these images, “Aerial” has a size of 256x256. The size of the others is 512x512. These images and their histograms are shown in Fig. 5.

The GWO-HS and other algorithms used for comparison were implemented in Python programming language. A computer with an Intel Core i7-9700K 3.6 GHz processor and 16 GB RAM was used for coding. The experiments were performed on the same computer. The parameter values used for the GWO-HS and other algorithms are given in Table 1. To make a fair comparison, the number of iterations of all algorithms was taken as 100. The population size of the GWO-HS, GA, GWO, HS and PSO algorithms was used as 100. The number of trials of the SA algorithm was determined as 100. Other parameter values of the algorithms were tuned by trial and error by conducting a series of preliminary experiments for each algorithm.

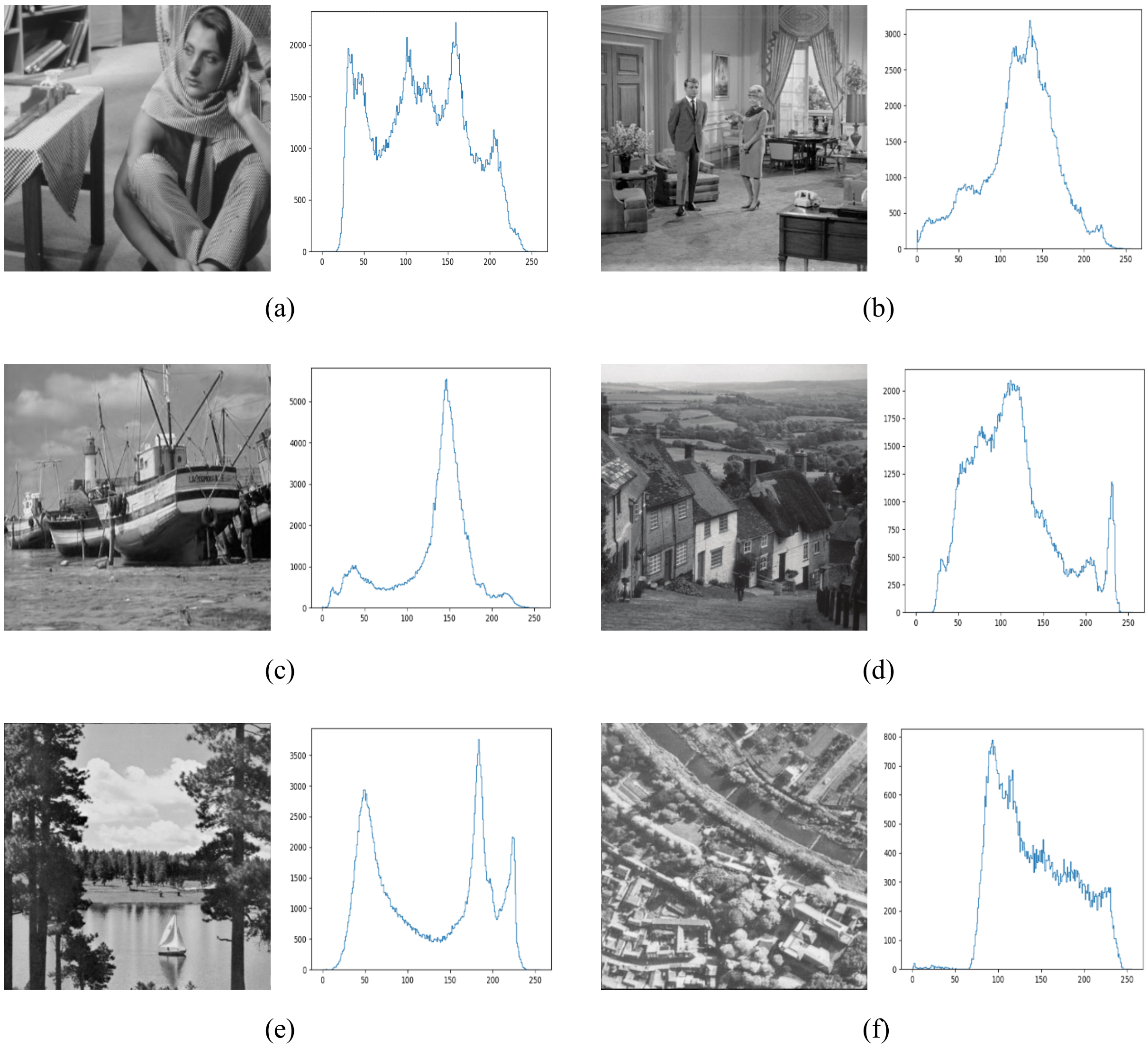


Figure. 5. *(a) Barbara, (b) Living room, (c) Boats, (d) Goldhill, (e) Lake, and (f) Aerial images and their histograms.*

Table 1. *The values of the parameters for the GWO-HS and other algorithms*

ALGORITHM	PARAMETERS
GA	Number of generations: 100, Population size: 100, Crossover rate: 0.80, Mutation rate: 0.30
GWO	Number of generations: 100, Number of gray wolves: 100, Distance control parameter a: Linearly decreased from 2 to 0
HS	Number of iterations: 100, Harmony memory size: 100, Harmony memory considering rate: 0.95, Pitch adjusting rate: 0.2, Bandwidth: 4.5, Bandwidth factor: 0.99
PSO	Number of iterations: 100, Number of particles: 100, Cognitive component: 2, Social component: 2, Inertia weight: 0.7, Inertia weight reduction rate: 0.99
SA	Number of iterations: 100, Number of trials: 100, Start temperature: 10, End temperature: 2
GWO-HS	Number of generations: 100, Number of gray wolves: 100, Distance control parameter a: Linearly decreased from 2 to 0, Bandwidth: 10

On each image, 50 independent runs were performed for threshold levels ranging from 2 to 10. The results obtained for the Otsu thresholding method are shown in Table 2 and the results obtained for the Kapur entropy-based thresholding method are shown in Table 3. In these tables, K is the number of thresholds, "Mean" is the mean value of 50 independent runs and "StdDev" is the standard deviation. The best values are shown in bold format.

As can be seen from Table 2, the proposed GWO-HS algorithm outperforms the GA, HS, PSO and SA algorithms for all threshold numbers on all images regardless of the number of thresholds. However, unlike the other algorithms, the performance of the GWO-HS algorithm against the GWO varies depending on the number of thresholds. While the GWO has a superior performance for low threshold levels such as 2, 3 and 4, the GWO-HS algorithm has a superior performance for all other threshold levels.

Table 2. *The comparison of the results obtained for the GWO-HS and other algorithms for the Otsu thresholding method.*

ALG.	K	BARBARA		LIVING ROOM		BOATS		GOLDHILL		LAKE		AERIAL	
		Mean	StdDev	Mean	StdDev	Mean	StdDev	Mean	StdDev	Mean	StdDev	Mean	StdDev
GA		2584.1910	2.4630	1620.4003	6.4055	1810.2318	15.2866	2076.6916	1.4500	3974.6408	3.6371	1795.0510	11.8624
GWO		**2608.6108**	**0.0000**	**1625.2673**	**0.0000**	**1823.1397**	**0.0000**	**2085.6947**	**0.0000**	**3977.5755**	**0.0000**	**1808.1711**	**0.0000**
HS	2	2601.8409	2.0570	1624.8008	0.3556	1821.7786	0.2735	2077.1936	0.0566	3973.7883	4.5642	1802.5479	4.7238
PSO		2235.3914	15.3925	1448.9853	136.0320	1681.5268	61.2415	1811.8681	58.7839	3813.9645	95.8014	1664.2596	65.8755
SA		2591.6760	12.5139	1618.2527	7.0140	1817.7942	3.7769	2070.2432	3.0542	3968.8791	2.3818	1796.3310	14.6802
GWO-HS		**2608.6108**	**0.0000**	**1625.2673**	**0.0000**	**1823.1397**	**0.0000**	2076.5756	**0.0000**	**3977.5755**	**0.0000**	**1808.1711**	**0.0000**
GA		2755.4494	1.1238	1733.3148	4.6643	1932.1339	1.0136	2207.9080	14.2830	4089.4587	2.5836	1879.0843	0.3126
GWO		**2785.1633**	**0.0000**	**1757.2036**	**0.0000**	**1954.0168**	0.0401	**2231.8820**	**0.0000**	**4115.4122**	**0.0207**	**1905.4106**	**0.0000**
HS	3	2772.9373	9.6976	1741.3981	5.8781	1941.0171	5.0339	2217.1816	16.6217	4102.5471	6.6054	1883.7208	3.8518
PSO		2404.1356	87.2914	1554.0675	79.4102	1706.8098	82.8380	1973.4373	8.6621	3826.3412	37.7550	1737.1064	75.2170
SA		2734.2633	2.0054	1698.5113	37.2179	1935.4507	9.8647	2203.0349	15.9237	4082.1568	16.4058	1847.5910	47.4007
GWO-HS		**2785.1633**	**0.0000**	1757.1092	0.1335	1954.0019	**0.0045**	2226.2436	0.2945	4115.3476	0.1120	1905.2183	0.0026
GA		2807.9848	33.9369	1785.1026	10.3733	1969.7063	11.9879	2276.5228	16.4350	4157.5134	20.2524	1926.1768	28.7448
GWO		**2856.1678**	**0.0494**	**1825.9301**	**0.1040**	**2014.3275**	**0.0332**	**2306.4799**	**0.0279**	**4184.1082**	**0.0012**	**1956.9222**	**0.0650**
HS	4	2822.5109	6.1322	1813.2851	7.0544	1999.3605	20.3531	2282.2977	17.5640	4170.2821	11.9938	1922.7369	11.1361
PSO		2517.6651	61.4201	1670.2290	6.3416	1709.7685	7.9745	2017.5602	42.2285	3877.9096	20.1863	1788.6861	83.8992
SA		2781.0431	40.1500	1793.8223	2.3193	1967.9787	38.1751	2265.9724	33.3402	4144.2550	37.5588	1941.2343	13.9038
GWO-HS		2855.8357	0.2530	1825.7420	0.1911	2014.2331	0.0628	2295.7821	4.7478	4183.7921	0.1084	1956.5352	0.1037
GA		2869.0107	2.2628	1824.7525	4.8468	2030.6021	14.8232	2317.0280	**0.0541**	4190.8097	5.1310	1961.0332	0.8955
GWO		2890.2421	0.4111	1858.0895	5.6760	**2049.1773**	**0.1123**	**2341.9834**	0.3901	4214.3206	5.4516	1972.7712	**0.1326**
HS	5	2876.2826	**0.2060**	1842.9403	**0.4044**	2030.8081	6.0340	2312.9102	6.3711	4196.7350	1.7866	1961.4944	7.3323
PSO		2580.8786	172.6711	1554.4679	133.9471	1746.7712	46.0661	1951.6828	29.0970	3897.6907	46.7089	1754.7712	111.1039
SA		2847.1356	8.6854	1829.7425	13.4999	2008.4857	9.0616	2282.8950	34.6408	4167.3238	27.1892	1953.2003	13.3505
GWO-HS		**2890.5733**	0.4252	**1865.2325**	3.1556	2045.4412	2.7995	2325.3024	4.3697	**4219.3742**	**0.3868**	**1980.4530**	0.1885
GA		2879.1309	0.9521	1874.8074	4.3155	2052.2617	2.1084	2340.7512	29.0965	4207.1812	25.2118	1973.9697	3.5615
GWO		2909.7850	1.4252	1891.2785	2.5665	2066.8545	2.9972	**2365.5163**	**0.2686**	4224.7625	6.9820	1985.9932	1.8952
HS	6	2889.8892	6.5527	1867.0588	16.9598	2051.9278	1.5615	2350.1437	4.3987	4223.8666	4.9657	1979.1305	5.7052
PSO		2530.3059	94.9214	1518.7585	49.9753	1780.9781	2.3210	2029.2863	30.5081	3890.0612	30.5334	1800.9264	79.2839
SA		2876.9104	24.2861	1858.4559	18.5598	2037.9610	11.9653	2327.9412	4.9404	4215.5165	4.2333	1968.7370	12.8693
GWO-HS		**2911.0586**	**0.7911**	**1892.7833**	**1.9265**	**2069.1918**	**1.3364**	2349.7007	5.4213	**4239.5216**	**0.8006**	**1996.3186**	**0.0163**
GA		2907.1388	0.4238	1889.3317	3.4316	2061.1949	2.5281	2356.7717	13.6920	4234.4416	6.7331	1986.9451	12.4362
GWO		**2926.4214**	2.8749	1899.0001	4.1339	2073.5523	1.5442	**2378.3609**	**1.8676**	4237.4688	18.3690	1992.3840	2.7788
HS	7	2912.9308	**0.0559**	1887.7824	3.1128	2062.1232	**0.0447**	2358.0746	3.2650	4237.0266	2.1384	1995.9981	3.1058
PSO		2546.5972	16.8260	1576.8282	8.7124	1772.0238	81.2900	1944.5262	75.6510	3924.0360	76.6665	1789.0999	12.6297
SA		2884.1001	20.6792	1879.7480	5.2222	2066.7447	11.5145	2351.5404	18.4830	4215.6697	10.9070	1970.4718	12.6682
GWO-HS		2924.7077	2.0174	**1908.6981**	**0.2393**	**2077.9682**	2.3875	2370.1317	4.1619	**4251.8789**	**0.0958**	**2009.2240**	**0.4069**
GA		2913.6766	2.5149	1895.9961	16.9940	2063.9027	4.0869	2362.8037	5.8789	4244.6577	6.5143	1998.1731	3.9611
GWO		2928.5480	10.0109	1910.5277	**0.0804**	2072.7483	3.7468	**2381.7524**	0.8584	4241.3426	**2.3105**	2005.0517	3.7883
HS	8	2909.8208	3.5274	1898.8606	1.2545	2076.0493	5.2671	2358.7956	0.8717	4246.6031	2.4043	2004.3405	5.3067
PSO		2546.1948	72.0733	1617.6435	93.5931	1792.3372	40.3141	1939.9588	126.2400	3947.2470	63.3169	1804.4573	49.3488
SA		2922.0381	15.5689	1904.0135	0.8376	2062.5634	1.3182	2365.2602	**0.2827**	4235.7993	12.9707	1995.5500	9.0327
GWO-HS		**2936.8981**	**0.7093**	**1914.3804**	3.3253	**2093.7253**	**0.6107**	2375.6113	7.4340	**4255.0859**	10.0895	**2018.3229**	**1.4666**
GA		2924.3481	1.6175	1911.3112	3.0668	2075.4618	6.0587	2378.1913	1.4432	4248.3892	4.0041	2014.3473	3.9541
GWO	9	2929.7747	6.3417	1909.5245	8.6469	2087.9356	3.2160	**2394.1818**	6.6303	4246.4588	4.6209	2008.5424	5.5828
HS		2928.4645	1.8576	1912.0299	**1.1043**	2084.3102	**1.1571**	2382.6090	2.7054	4255.1563	5.4818	2010.2094	2.6260

PSO		2513.6373	61.6789	1605.1585	67.7974	1874.6807	1.8210	2080.9371	31.6025	3929.3808	52.1731	1809.6216	13.8751
SA		2923.7228	3.2142	1898.2830	1.1253	2080.0399	1.7578	2373.4272	5.5579	4245.9283	13.9104	2003.3753	2.7279
GWO-HS		**2944.7483**	**0.2524**	**1928.1072**	1.6900	**2097.7919**	4.0696	2384.8441	**0.8086**	**4269.2838**	**0.0162**	**2024.6727**	**2.1029**
GA	10	2927.8068	2.8613	1914.1002	16.6783	2087.0520	2.1316	2380.8974	12.7005	4258.4818	**0.0321**	2005.3658	5.2694
GWO		2943.4035	1.8916	1915.2266	**0.8322**	2089.5607	**0.5032**	**2395.6620**	7.4484	4256.7845	3.1528	2012.6915	4.7114
HS		2934.1225	1.1725	1916.2005	7.6420	2090.3541	4.6657	2385.1949	**3.5443**	4257.1314	1.5684	2012.0261	4.9177
PSO		2484.5586	50.5821	1668.2146	70.1665	1822.5785	39.5544	2100.4246	18.2842	3851.8372	1.4674	1814.7564	**1.4517**
SA		2915.1557	4.5359	1910.9725	15.7211	2084.2187	8.9720	2370.0133	6.3657	4248.2276	0.7648	1998.4395	10.5941
GWO-HS		**2949.8372**	**0.6889**	**1925.1168**	2.0616	**2101.7355**	5.4750	2385.2922	7.7805	**4272.5863**	2.4680	**2026.8107**	1.9890

A similar situation to that in Table 2 is also seen in Table 3. The proposed GWO-HS algorithm outperforms the GA, HS, PSO and SA algorithms for all threshold numbers on all images regardless of the number of thresholds. However, unlike the other algorithms, the performance of the GWO-HS algorithm against the GWO varies depending on the number of thresholds. While the GWO has a superior performance for low threshold levels such as 2, 3 and 4, the GWO-HS algorithm has a superior performance for all other threshold levels.

Table 3. *The comparison of the results obtained for the GWO-HS and other algorithms for the Kapur entropy-based thresholding method.*

ALG.	K	BARBARA		LIVING ROOM		BOATS		GOLDHILL		LAKE		AERIAL	
		Mean	StdDev	Mean	StdDev	Mean	StdDev	Mean	StdDev	Mean	StdDev	Mean	StdDev
GA	2	12.6252	0.0235	12.6660	0.0369	12.5093	0.0801	12.5492	0.0136	12.5147	0.0158	12.5090	0.0345
GWO		**12.6683**	**0.0000**	**12.7019**	**0.0000**	**12.6193**	**0.0000**	**12.5606**	**0.0000**	**12.5293**	**0.0000**	**12.5382**	**0.0000**
HS		12.6582	0.0139	12.6964	0.0004	12.6079	0.0023	12.5492	0.0019	12.5130	0.0096	12.4908	**0.0000**
PSO		11.9384	0.3238	12.1306	0.3024	11.6006	0.4765	12.2879	0.1572	11.5890	0.0515	11.4848	0.2978
SA		12.6544	0.0097	12.6963	0.0058	12.5685	0.0540	12.5393	0.0170	12.4656	0.0540	12.4907	0.0272
GWO-HS		**12.6683**	**0.0000**	12.7018	0.0002	**12.6193**	**0.0000**	**12.5606**	**0.0000**	**12.5293**	**0.0000**	12.5294	0.0124
GA	3	15.6687	0.0104	15.7825	0.0201	15.8082	0.0005	15.5748	0.0308	15.3709	0.0410	15.6307	0.0872
GWO		**15.7471**	**0.0000**	**15.9444**	**0.0000**	**15.8794**	**0.0000**	15.6406	0.0001	**15.5702**	**0.0000**	**15.7519**	**0.0000**
HS		15.7220	0.0018	15.8887	0.0273	15.7576	0.0434	15.6235	0.0211	15.5141	0.0047	15.6724	0.0595
PSO		13.5706	0.2520	14.1911	0.5221	14.5628	0.4143	13.8414	0.1084	14.3647	0.4960	13.5593	0.3798
SA		15.6001	0.0339	15.8547	0.1046	15.7921	0.0153	15.5335	0.0256	15.4195	0.1474	15.6188	0.0814
GWO-HS		15.7466	0.0007	15.9431	0.0009	15.8769	0.0011	**15.6407**	**0.0000**	**15.5702**	**0.0000**	15.7497	0.0026
GA	4	18.3988	0.0664	18.8190	0.0098	18.6197	0.1121	18.2525	0.0198	18.2935	0.0832	18.1531	0.1048
GWO		**18.5563**	**0.0007**	**18.9463**	**0.0013**	**18.7385**	**0.0001**	**18.4494**	**0.0000**	**18.3767**	**0.0002**	**18.6156**	**0.0004**
HS		18.4293	0.0587	18.8272	0.0771	18.4860	0.0157	18.3345	0.0541	18.2386	0.0848	18.4334	0.1023
PSO		16.5959	0.0817	15.3886	1.2257	15.6612	0.3071	15.1331	0.0259	15.7522	0.3322	15.9201	0.9681
SA		18.2764	0.0254	18.7200	0.0671	18.4472	0.0365	18.1877	0.1772	18.0875	0.1197	18.4365	0.1741
GWO-HS		18.5523	0.0059	18.9398	0.0074	18.7339	0.0060	18.4470	0.0015	18.3379	0.0530	18.6016	0.0118
GA	5	20.9457	0.0658	21.3724	0.0952	21.2435	0.1010	20.9026	0.0029	20.6284	0.0497	20.5493	0.1304
GWO		**21.2400**	0.0024	21.7153	**0.0029**	**21.4426**	**0.0004**	**21.1419**	0.0047	21.0244	0.0083	21.0572	0.0847
HS		21.0481	0.0344	21.4247	0.1468	21.1837	0.0876	20.8837	0.0216	20.7001	0.1097	20.9696	0.0764
PSO		17.8725	1.0216	17.2073	0.8951	17.2145	0.4701	18.2866	0.0842	17.3896	0.4069	16.3488	0.8178
SA		20.7161	0.5950	21.4145	0.0620	21.1040	0.0352	20.6740	**0.0018**	20.5511	0.2749	20.7201	0.0771
GWO-HS		21.2393	**0.0002**	**21.7178**	0.0143	21.3627	0.1160	21.1402	0.0062	**21.0266**	**0.0066**	**21.2009**	**0.0054**
GA	6	22.9331	0.0136	23.9098	0.0364	23.6021	**0.0082**	23.0935	0.4586	22.9126	0.1436	23.1356	0.1157
GWO		**23.7831**	0.0072	24.3078	0.0212	23.9588	0.0194	**23.6636**	0.0071	23.2158	0.0447	**23.5513**	**0.0065**
HS		23.4492	0.0280	24.0895	0.0977	23.7495	0.0559	23.0830	**0.0033**	22.9928	0.0416	23.3061	0.0903
PSO		18.0581	0.9312	18.7883	0.4069	18.6541	1.5392	20.3779	0.6459	17.5753	1.9682	17.7612	0.5998
SA		23.2091	0.1397	23.8253	0.0829	23.3524	0.2198	22.9735	0.3934	22.9717	0.1874	23.1749	0.0281
GWO-HS		23.7737	**0.0047**	**24.3545**	**0.0079**	**23.9723**	0.0532	23.6345	0.0440	**23.4788**	**0.0144**	23.5147	0.0265
GA	7	25.7626	0.1925	26.3365	0.3389	26.2180	0.2513	25.3754	0.1254	24.9614	0.1979	25.4197	0.0845
GWO		26.0397	0.1081	26.6397	0.1980	**26.4550**	**0.0109**	**25.9749**	0.0250	**25.7415**	**0.0204**	25.4750	0.0657
HS		25.5607	0.3158	26.5017	**0.0411**	26.0511	0.0942	25.4976	0.0913	25.1428	0.0874	25.5489	0.2046
PSO		18.9002	0.2706	20.2183	0.1047	17.1257	1.0049	18.7328	1.2450	17.9422	0.2071	18.2603	1.5876
SA		25.5015	0.0711	26.4212	0.1039	25.9455	0.2192	24.8579	0.2349	24.9165	0.0230	24.8996	0.2837

GWO-HS		**26.1013**	**0.0294**	**26.8286**	0.1229	26.4246	0.1135	25.9689	**0.0140**	25.5536	0.1831	**25.8131**	**0.0645**
GA	8	27.2037	0.2271	28.8348	0.1241	28.2435	0.0852	27.3205	0.8197	26.8099	0.3684	26.9369	0.1745
GWO		28.1418	0.3203	29.0141	0.1976	28.6826	**0.0583**	28.1022	0.0859	27.9591	**0.0075**	27.4680	0.0637
HS		27.6178	**0.0092**	28.9876	**0.0500**	28.3939	0.2583	27.9004	0.0827	27.8550	0.0362	27.5557	0.2222
PSO		20.7313	0.4980	20.8748	1.3729	21.0877	0.5928	19.8148	0.7161	19.1393	0.1075	20.4393	0.8429
SA		27.5086	0.0615	28.2828	0.0992	28.0041	0.5507	26.7687	0.3206	27.0479	0.1589	26.9273	0.1544
GWO-HS		**28.4319**	0.0317	**29.2446**	0.1423	**28.7958**	0.1471	**28.1558**	**0.0595**	**27.9691**	0.1791	**27.9824**	**0.0240**
GA	9	29.3344	0.0500	30.6411	0.2088	30.3648	0.0238	29.1254	0.7867	29.0889	0.5094	28.5324	0.1392
GWO		29.8239	0.1504	30.6994	0.5002	30.2035	0.0528	29.9995	**0.0161**	29.7540	0.0746	29.3662	0.0801
HS		29.8402	0.1663	31.1597	0.0963	30.3691	0.0841	29.7164	0.0865	29.6150	0.2811	29.1923	0.2746
PSO		20.9682	1.5874	20.2820	0.9219	20.1675	1.6202	20.3027	0.8412	21.0034	1.7656	19.0573	0.7041
SA		29.1280	0.4675	30.3695	0.1227	30.5642	**0.0155**	29.0973	0.1094	28.7461	0.4776	28.8279	0.4483
GWO-HS		**30.3580**	**0.0210**	**31.6520**	**0.0178**	**31.0191**	0.0806	**30.0713**	0.3344	**30.1692**	**0.0742**	**30.0533**	**0.0470**
GA	10	31.6385	0.2498	32.9102	**0.0099**	32.3071	0.5693	30.7238	0.5646	30.8563	0.0992	31.2848	0.2417
GWO		31.6653	0.1355	32.2359	1.3386	31.3490	0.4856	31.4680	0.0655	31.5623	0.0550	31.5523	**0.0019**
HS		31.4221	0.0954	32.9657	0.5832	32.3508	0.2083	31.2785	0.2643	31.4129	0.0748	31.6459	0.2342
PSO		19.8090	1.6787	19.2198	0.1125	19.6690	0.3800	20.2807	0.9136	20.0017	0.5122	20.8569	1.1840
SA		30.3055	0.1730	32.1957	0.1128	32.1674	0.3856	30.1846	**0.0123**	31.0393	**0.0522**	30.9646	0.0353
GWO-HS		**32.3877**	**0.0424**	**33.7634**	0.0772	**33.0430**	**0.0400**	**32.1353**	0.0962	**32.2085**	0.0590	**31.7871**	0.4446

Considering the values in Tables 2 and 3, the numbers of obtaining the best value for all threshold levels of each algorithm were calculated and presented in Table 4. As can be seen from this table, the proposed GWO-HS algorithm has obtained equal or better values in 9 out of 12 values for the Otsu and Kapur entropy-based thresholding methods. After the results of the GWO-HS, the best results belong to the GWO, which are 4 and 7 for the Otsu and Kapur entropy-based thresholding methods, respectively.

Table 4. *The number of times the GWO-HS and other algorithms achieve the best value.*

METHOD	ALG.	BARBARA		LIVING ROOM		BOATS		GOLDHILL		LAKE		AERIAL	
		Mean	StdDev	Mean	StdDev	Mean	StdDev	Mean	StdDev	Mean	StdDev	Mean	StdDev
OTSU	GA	-	-	-	-	-	-	-	1	-	1	-	-
	GWO	4	3	3	**5**	4	**4**	**9**	**5**	3	4	3	4
	HS	0	2	-	2	0	2	-	1	-	-	-	-
	PSO	-	-	-	-	-	-	-	-	-	-	-	1
	SA	-	-	-	-	-	-	-	1	-	-	-	-
	GWO-HS	**7**	**6**	**7**	3	**6**	**4**	-	2	**7**	**5**	**7**	**5**
KAPUR ENTROPY-BASED	GA	-	-	-	1	-	1	-	-	-	-	-	-
	GWO	**5**	3	3	**4**	**5**	**6**	**5**	3	4	**5**	4	**5**
	HS	-	1	-	2	-	-	-	1	-	-	-	1
	PSO	-	-	-	-	-	-	-	-	-	-	-	-
	SA	-	-	-	-	-	1	-	2	-	1	-	-
	GWO-HS	**5**	**6**	**6**	2	**5**	2	**5**	**4**	**7**	**5**	**5**	4

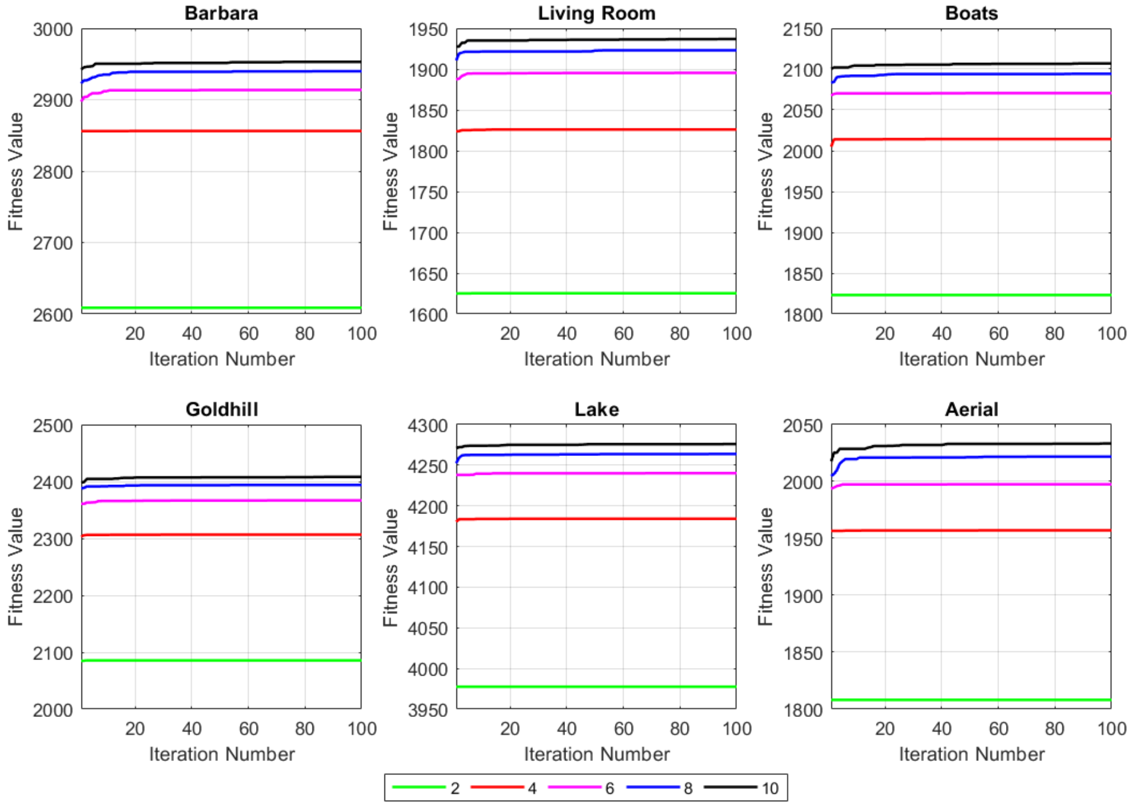
In Table 5, the threshold values determined by the GWO-HS algorithm are given for threshold levels ranging from 2 to 10 for the Otsu and Kapur entropy-based thresholding methods. These values are threshold values for the best result in 50 runs.

Fig. 6 illustrates the convergence curves obtained on all test images of the proposed GWO-HS algorithm. Fig. 6a shows the convergence curves obtained with the Otsu thresholding method for threshold levels of 2, 4, 6, 8, and 10, while Fig. 6b shows the convergence curves obtained with the Kapur entropy-based thresholding method for the same threshold levels. As can be seen from both figures, the proposed GWO-HS algorithm converges quickly for low threshold levels. For large threshold levels, the convergence of the GWO-HS algorithm is fast in the first half of the iterations, while it is slower in the second half.

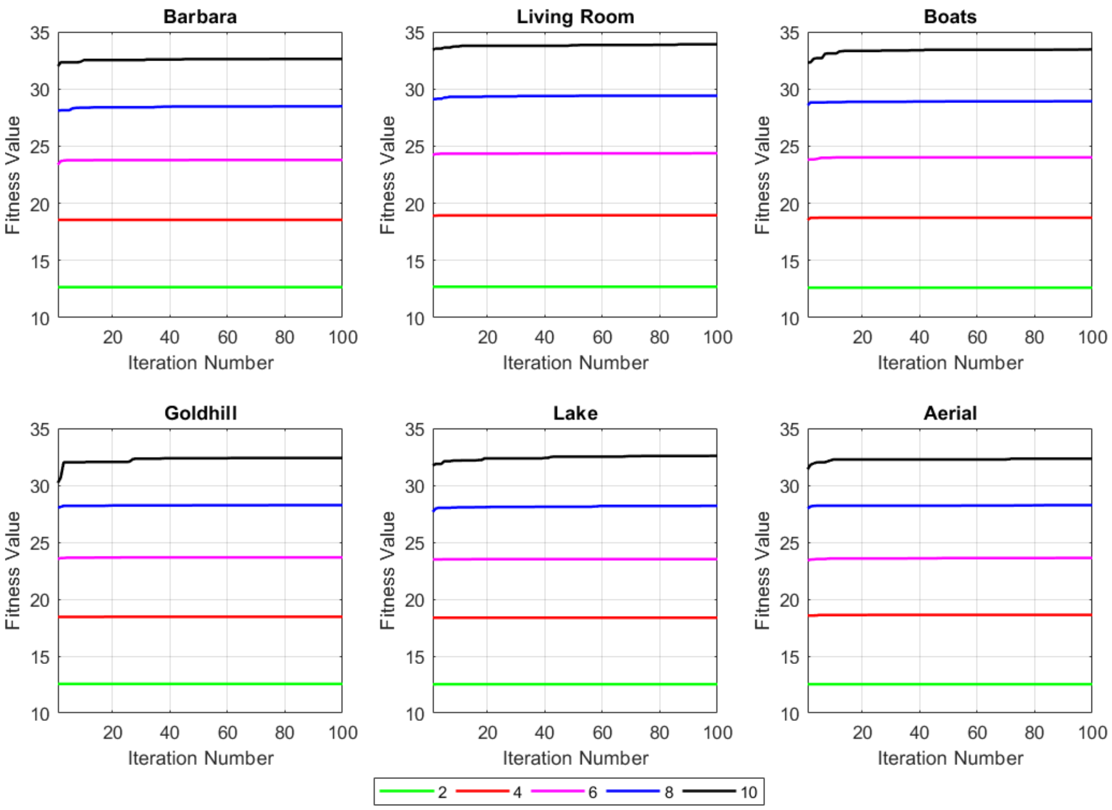
Table 5. *The threshold values determined by the GWO-HS algorithm.*

IMAGES	K	THRESHOLD VALUES

		Otsu	Kapur Entropy-Based
	2	82, 147	96, 168
	3	75, 127, 176	76, 127, 178
	4	66, 106, 142, 182	60, 99, 141, 185
	5	57, 88, 118, 148, 184	58, 95, 133, 172, 210
BARBARA	6	54, 84, 112, 140, 167, 195	55, 87, 119, 151, 185, 221
	7	46, 70, 95, 118, 143, 169, 196	53, 82, 111, 140, 168, 194, 221
	8	45, 68, 91, 112, 133, 153, 174, 199,	49, 73, 97, 122, 147, 172, 196, 222
	9	42, 61, 81, 100, 118, 137, 156, 177, 201	45, 67, 88, 109, 131, 153, 176, 199, 222
	10	41, 59, 78, 96, 114, 132, 149, 167, 186, 207	42, 61, 80, 103, 123, 143, 162, 180, 200, 222
	2	86, 144	91, 172
	3	76, 124, 163	47, 104, 176
	4	57, 98, 133, 169	47, 99, 150, 197
	5	49, 89, 121, 147, 179	44, 88, 128, 167, 200
LIVING ROOM	6	41, 75, 104, 128, 152, 182	41, 84, 122, 161, 198, 236
	7	38, 71, 99, 122, 142, 163, 190	37, 71, 102, 137, 169, 200, 236
	8	36, 66, 92, 112, 129, 147, 167, 193	28, 55, 83, 111, 142, 171, 200, 236
	9	34, 60, 82, 103, 121, 136, 153, 172, 197	25, 49, 75, 100, 125, 150, 176, 202, 236
	10	29, 52, 73, 93, 110, 125, 140, 156, 176, 201	22, 44, 66, 88, 110, 134, 159, 182, 204, 236
	2	93, 155	109, 179
	3	73, 126, 167	63, 120, 179
	4	67, 116, 149, 181	51, 91, 129, 179
	5	54, 95, 129, 154, 184	50, 90, 128, 166, 195
BOATS	6	46, 81, 115, 139, 158, 187	51, 90, 126, 163, 193, 227
	7	43, 74, 105, 130, 148, 165, 193	34, 65, 98, 129, 164, 193, 227
	8	38, 65, 94, 119, 138, 153, 169, 195	31, 61, 94, 125, 154, 178, 204, 234
	9	32, 55, 80, 106, 127, 143, 156, 173, 198	28, 55, 81, 105, 130, 155, 178, 204, 234
	10	31, 54, 78, 102, 123, 138, 150, 162, 178, 201	24, 45, 66, 89, 111, 131, 157, 179, 204, 234
	2	94, 161	91, 158
	3	83, 126, 179	79, 134, 181
	4	69, 102, 138, 186	64, 103, 144, 188
	5	63, 91, 117, 147, 191	59, 95, 132, 166, 200
GOLDHILL	6	61, 88, 112, 138, 171, 207	45, 74, 104, 135, 167, 200
	7	56, 79, 100, 120, 144, 176, 211	45, 72, 100, 128, 153, 178, 205
	8	51, 71, 91, 111, 131, 153, 181, 212	43, 66, 89, 112, 136, 160, 185, 210
	9	48, 67, 85, 102, 118, 137, 159, 186, 214	43, 65, 87, 108, 130, 153, 174, 195, 217
	10	45, 64, 80, 96, 110, 125, 142, 163, 188, 214	41, 60, 78, 97, 116, 135, 155, 174, 195, 216
	2	85, 154	91, 163
	3	78, 140, 194	73, 120, 170
	4	67, 110, 158, 198	69, 112, 157, 195
	5	57, 88, 128, 167, 200	62, 96, 131, 166, 198
LAKE	6	51, 74, 104, 139, 171, 201	37, 69, 102, 135, 168, 199
	7	49, 70, 97, 129, 161, 184, 205	37, 65, 91, 118, 146, 172, 200
	8	46, 64, 86, 112, 141, 168, 189, 209	13, 37, 64, 91, 118, 145, 171, 199
	9	43, 59, 77, 99, 124, 151, 173, 191, 210	13, 35, 60, 82, 105, 128, 151, 174, 201
	10	39, 54, 70, 88, 110, 134, 157, 175, 191, 210	13, 34, 58, 80, 102, 124, 147, 170, 191, 211
	2	125, 178	68, 159
	3	109, 147, 190	68, 130, 186
	4	104, 134, 167, 202	68, 117, 159, 200
	5	99, 123, 148, 175, 205	68, 108, 141, 174, 207
AERIAL	6	61, 101, 125, 150, 177, 206	68, 101, 128, 156, 184, 212
	7	54, 97, 116, 137, 161, 185, 210	31, 68, 101, 128, 156, 184, 212
	8	54, 93, 109, 127, 147, 168, 189, 212	31, 68, 98, 123, 148, 170, 194, 216
	9	49, 91, 106, 122, 139, 157, 176, 195, 216	31, 68, 94, 117, 137, 158, 178, 200, 221
	10	56, 90, 104, 119, 134, 150, 166, 183, 201, 219	27, 68, 84, 102, 119, 139, 160, 181, 201, 222



(a)



(b)

Figure. 6. *The convergence curves for the Otsu and Kapur entropy-based thresholding methods of the proposed GWO-HS algorithm*

CONCLUSIONS

In this paper, a hybrid algorithm called GWO-HS was proposed to solve the multi-level image thresholding problem. The proposed algorithm was obtained by hybridizing the GWO and HS algorithms. The performance of the GWO-HS algorithm was compared with the performance of basic algorithms such as the GA, GWO, HS, PSO and SA. The Otsu and Kapur entropy-based thresholding methods were used in the comparisons. “Barbara”, “Living room”, “Boats”, “Goldhill”, “Lake” and “Aerial” images were used in the experiments. Thresholding was applied on each image for threshold levels ranging from 2 to 10. The results showed that the proposed GWO-HS algorithm has a superior performance compared to other algorithms, especially for high threshold levels.

In the future, the performance of the proposed GWO-HS algorithm can be improved, especially for low threshold levels. Also, the GWO algorithm can be hybridized with another basic algorithm to develop a completely new hybrid algorithm.

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