P- ISSN 1991-8941 E-ISSN 2706-6703 2023,(17), (1):137– 148 *Journal of University of Anbar for Pure Science (JUAPS)* Open Access

Optimization Methods for Image Thresholding: A review

Bushra A. Abd*, Azmi T. Hussein Alrawi, Atheer Bassel

University of Anbar College of Computer Science and Information Technology Department of Computer Science

ARTICLE INFO
Received: 06 / 12 /2022
Accepted: 27 / 01/ 2023
Available online: 12 / 06 / 2023

DOI: 10.37652/juaps.2023.178875

Keywords:
Method of Thresholding,
The optimization algorithms,
Simulated Annealing,
Jaya.

ABSTRACT

Setting a border with the proper gray level in processing images to separate objects from their backgrounds is crucial. One of the simplest and most popular methods of segmenting pictures is histogram-based thresholding. Thresholding is a common technique for image segmentation because of its simplicity. Thresholding is used to separate the Background of the image from the Foreground. There are many methods of thresholding. This paper aims to review many previous studies and mention the types of thresholding. It includes two types: the global and local thresholding methods and each type include a group of methods. The global thresholding method includes (the Otsu method, Kapur's entropy method, Tsallis entropy method, Hysteresis method, and Fuzzy entropy method), and the local thresholding method includes (Ni-Black method and Bernsen method). The optimization algorithms(Genetic Algorithm, Particle Swarm Optimization, Bat Algorithm, Modified Grasshopper Optimization, Firefly Algorithm, Cuckoo Search, Tabu Search Algorithm, Simulated Annealing, and Jaya Algorithm) used along with thresholding methods are also illustrated.

1. Introduction

The process of splitting a digital image into various groupings of pixel sets is known as image segmentation. In various applications that employ image processing, segmentation is an essential first step for image analysis and visualization. Making each image sample simpler or more amenable to straightforward analysis is the major goal of image segmentation[1].

Target recognition begins with image segmentation, in which the objects are separated from the Background. Image segmentation's primary goal is to streamline and transform the relevant sample of the image into a simply understandable image. Bilevel thresholding or several multilevel thresholds are used in image segmentation. Images can be segmented using various methods, such as the Hough transformation, neural networks, template matching, and threshold[2].

One of the simplest and most direct methods for segmenting images is thresholding.

Thresholding is a direct method for extracting several sections from an image due to its simplicity.

The purpose of thresholding [3] and simplicity make it a popular technique for segmenting images. Thresholding separates an image's Background from its Foreground [1].

Thresholding with optimization algorithms (Several modified optimization algorithms with multilevel thresholds) has been used to find the image's optimal thresholding values and improve the thresholding's global performance.

This paper deals with many thresholding methods used in image segmentation, including Otsu, Kapur, Hysteresis, Homogeneity, Fuzzy, LOCAL, etc. In addition, this study presents previous studies, each method with its use, and the results obtained. A contribution of this paper is to make a review of the thresholding methods. It also includes thresholding challenges and applications.

*Corresponding author at: Department of Computer Science, College of Computer Science and Information Technology at the University of Anbar;ORCID:https://orcid.org/0000-0000-00000- ;Tel:+ .:+9647811315656
E-mail address: bus20c1004@uoanbar.edu.iq

The paper is organized as follows: Section 2 addresses the related work. The methods of thresholding are shown in section 3. Applications of thresholding with optimization **are dealt with** in section 4. In Section 5, the conclusion is presented.

2. Literature Work

Due to its simplicity, thresholding is one of the most used methods for segmenting images. Thresholding differentiates an image's Background from its Foreground [1].

Ping-Sung Liao et al. (2001) state that a quicker variant of Otsu's method is suggested to increase the effectiveness of computing the ideal thresholding for an image. Compared to the traditional Otsu method, this method can reduce processing time from more than an hour to less than 107 seconds [3].

Kezong Tang et al. (2011) affirm that the multilevel thresholding color image segmentation challenge was used to present the cuckoo search algorithm. The optimization phase of multilevel MCET used an improved genetic algorithm-based approach for thresholding selection. Recursive programming is utilized to reduce the computational complexity of the objective function in multilevel minimum cross entropy thresholding (MCET) by incorporating it into a genetic algorithm. Depending on the use of the genetic algorithm, the searching for the best thresholding. Bilevel and multilevel thresholding were both considered. The results of testing and the suggested method on various types of images demonstrate that it is effective and practical for the use with actual images[4].

Debashis M et al. (2014) argue that particle swarm optimization (PSO) is one of the bio-inspired optimization algorithms proposed for segmenting and analyzing medical images. In medical imaging, PSO is able to provide an optimum threshold value within an efficient time frame. The suggested method assists medical professionals or doctors in detecting various things, such as tumors and calculi in ultrasound images or fractures or ligament tears in any X-ray report[5].

A. K. Bhandari et al. (2016) said that the problem of multilevel thresholding color image segmentation is addressed using cuckoo search strategies; Otsu or Kapur's methods are used when optimizing solutions. The proposed method has been evaluated by comparing its results to those obtained with three additional nature-inspired methods. Determining the best solution and evaluating its fitness values along with four well-known performance metrics - PSNR, MSE, SSIM, and FSIM - has been done qualitatively and quantitatively based on differential evolution, wind-driven optimization (WDO), and particle swarm optimization (PSO). For segmenting multilevel colored satellite images, Kapur's entropy proved more accurate and robust than various nature-inspired optimization techniques. As opposed to this, the cuckoo search proved to be the most effective method of segmenting colored satellite images [6].

Mohamed A et al. (2017) state that a Moth-Flame Optimization (MFO) and Whale Optimization Algorithm (WOA) are proposed for image segmentation to determine the best multilevel thresholding. The proposed methods have been tested using a variety of benchmark (test) images to address the issue of the lengthy time it takes the multilevel threshold to select the optimal threshold. The findings were examined using the best fitness values, PSNR, SSIM measurements, the ANOVA test, and time complexity. Additionally, the MFO outperformed the WOA in terms of results [7].

A. AHILAN et al. (2019) said that Fragmentary Order For telemedicine applications, Darwinian Particle Swarm Optimization (FODPSO) present a multilevel thresholding method based on optimization techniques for extracting regions of interest and compressing DICOM images. According to the simulation results, FODPSO-based multilayer level thresholding produces better outcomes[8].

A. Ramya et al. (2019) argue that a novel framework for noise reduction and detection has been proposed. There are two phases to this structure. The noise detection phase, which is the first step, is carried out using the recently described adaptive multi-thresholding approach (AMT). The edge-preserving median filter (EPM), which controls the blurring effect while keeping the fine details of the interior region, is used to modify the noisy pixel in the second phase. With benchmark images and medical images, the planned work is evaluated[9].

P- ISSN 1991-8941 E-ISSN 2706-6703 Journal of University of Anbar for Pure Science (JUAPS) Open Access
2023,(17), (1):137– 148

Guoshen Ding et al.(2019) have proposed an effective multilevel image thresholding solution by incorporating a hybrid adaptive-cooperative learning strategy with an upgraded FOA algorithm. As a result, the goal is to increase optimization performance and problem-solving accuracy without triggering FOA's local optimum. HACLFOA fruit fly individuals have a powerful global search capability thanks to the controlling factor, and due to the regulatory factor, they can focus their exploration efforts on a local area. By balancing global search abilities with local search abilities, this adaptive learning strategy can be used. Additionally, the fruit fly individual is tested by the HACLFOA algorithm not only as a total item but also as an individual in each dimension during the optimizing process, which increases the solving accuracy of the algorithm[10].

Wei Liu et al. (2020) show that a meta-heuristic approach was used to find the best thresholding values for segmenting images based on the breeding process of Chinese hybrid rice. The fitness function was Renyi's entropy, and four standard image sets and four SEM images of cement were used to determine the best thresholding values. Based on standard and microscopic images of cement, HRO-Renyi has a better PSNR and SSIM, indicating a better fit for threshold segmentation[11].

Shikai Wang et al. (2021) suggest using an ant lion optimizer algorithm for multilevel thresholding color image segmentation. Otsu and Kapur's entropy is chosen from a variety of thresholding segmentation techniques. They serve as objective processes. The complexity of time increases exponentially as the number of thresholds rises. A modified ant lion optimizer method based on opposition-based learning (MALO) is presented to solve this problem by determining the ideal threshold values via maximization of the objective functions. A number of experiments conclusively demonstrate that the MALO method has higher search accuracy and convergence speed, making it a powerful and effective thresholding tool. The introduction of the opposition-based learning technique improves search accuracy and convergence performance[12].

3. Methods OF Thresholding

There are several thresholding methods used in image segmentation, as shown in Figure 1:

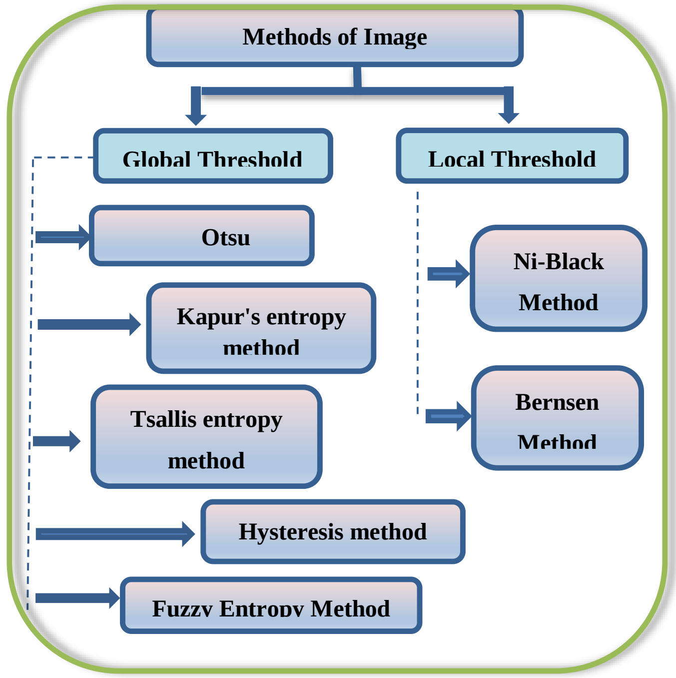

Fig 1: Methods oF Thresholding.

During the processing of images, segmentation is a crucial step. It is the division of the image pixels into various regions based on the information about their intensity and threshold value[13]. The thresholding uses several methods to segment images, and they are used in the medical and other fields, and these methods are:

3.1. Global Thresholding

The global thresholding method can be most effective when the target items create distinct peaks in the image's gray-level histogram. Based on the characteristics of its nearby pixels, the methods calculate a threshold value for each pixel. The methods that use global thresholding are more noise-sensitive. Various global thresholding methods have been presented[14], As explained below:

3.1.1 Otsu Method

A non-parametric segmentation process called the Otsu method (Between-class variance) divides the image into several classes[15]. The fundamental idea

behind this method is to divide an image's pixels into two groups. Otsu method has been applied by numerous researchers [16].
The inter-class variance function is described by Eq (1)[17].

$$\sigma_0^2 = \omega_0(\mu_0 + \mu_T)^2 . \sigma_1^2 = \omega_1(\mu_1 + \mu_T)^2 . \cdots . \sigma_m^2 = \omega_m(\mu_m + \mu_T)^2 \quad (1)$$

Where

$$\mu_0 = \frac{\sum_{i=0}^{t_1-1} iP_i}{\omega_0} . \mu_1 = \frac{\sum_{i=t_1}^{t_2-1} iP_i}{\omega_1} . \cdots . \mu_m = \frac{\sum_{i=t_m}^{N-1} iP_i}{\omega_m} \quad (2)$$

Where, $\mu_0 . \mu_1 . \cdots\cdots . \mu_m$ = the average intensity value of the pixel of class 0, 1, ⋯⋯, m respectively, for multilevel thresholding.

μ_T = global mean.

P_i = probable pixel intensity value of i of spectrum 0 to 255

N = sum of different intensity levels.

As a result, the segmentation technique attempts to raise f(t), which specifies the sum of the inter-class variance function, to obtain the defined peak threshold values at Eq (3) [17].

$$\overrightarrow{t^*} = \arg\max\big(f(t)\big) \quad Where\ f(t) = \sum_{i=0}^{m} \sigma_i^2 \quad (3)$$

This method applies to both grayscale and color images.

3.1.2 Entropy criterion method (Kapur's method)

In this method, the goal is to determine the optimal threshold value for increasing total entropy. Based on the entropy calculation, An image can be separated into classes and compressed [13].

Kapur's method can also be expanded to multilevel thresholding; it can be formulated as seen below[18]:

$$f(t_1 . t_2 . \cdots\cdots . t_n) = H_0 + H_1 \cdots\cdots + H_n \quad (4)$$

Where

$$H_0 = -\sum_{i=0}^{t_1-1} \frac{P_i}{\omega_0} \ln \frac{P_i}{\omega_0} . \omega_0 = \sum_{i=0}^{t_1-1} P_i$$

$$H_1 = -\sum_{i=t_1}^{t_2-1} \frac{P_i}{\omega_1} \ln \frac{P_i}{\omega_1} . \omega_1 = \sum_{i=t_1}^{t_2-1} P_i$$

$$H_2 = -\sum_{i=t_2}^{t_3-1} \frac{P_i}{\omega_2} \ln \frac{P_i}{\omega_2} . \omega_2 = \sum_{i=t_2}^{t_3-1} P_i$$

$$H_n = -\sum_{i=t_n}^{L-1} \frac{P_i}{\omega_n} \ln \frac{P_i}{\omega_n} . \omega_n = \sum_{i=t_n}^{L-1} P_i$$

Maximizing the objective function yields the optimal thresholds, that is[19]:

$$t^* = \arg \max(f(t_1 . t_2 . \cdots\cdots t_n)) \quad (5)$$
$$0 \le t \le L-1$$

where L is the total number of different intensity levels in the grayscale image and H0, H1,... Hn is the entropy value of the n + 1 various regions or classes. Pi is the probability that the pixel intensity value will be in the range of 0 to 255. It can be used to segment color images by processing the R, G, and B channels independently.

3.1.3 Tsallis Entropy Method

Shannon's entropy has been updated to Tsallis's entropy. Shannon initially used entropy to estimate the system's ambiguous information content. Normally, entropy is used to assess how chaotic a system is [20]. Tsallis has proposed generalizing Boltzmann-Gibbs (BGS) statistics based on multi-fractal theory[13], and the expression can be described as

$$S_q = \frac{1-\sum_{i=1}^{k}(p_i)^q}{q-1} \quad (6)$$

where k is the total number of system possibilities, q is an entropic index describing the degree of nonextensivity, and I p is a number between 0 and 1, indicating the likelihood that the modelled system will be in state i.

A pseudo-additivity entropic rule can be used to calculate the system's Tsallis entropy using Eq (7)[17][21]:

$$S(f_g^c + b_g^c) = S_q(f_g^c) + S_q(b_g^c) + (1-q) . S_q(f_g^c) . S_q(b_g^c)$$

$$C = \begin{cases} 1.2.3 & if \quad RGB\ image \\ 1 & if \quad gray\ scale\ \ image \end{cases} \quad (7)$$

Where,

f_g^c =Foreground of an image.

b_g^c =Background of an image.

Where the Foreground and Background of an image are indicated by f g and bg, you can segment grayscale and color images with this method. Tsallis entropy method multilevel (m-level) image thresholding can so be stated as:

$$S_q^{C_0}(t) = \frac{1-\sum_{i=0}^{t1-1}(P_i^C\,|P^{C_0})^q}{q-1};$$

$$S_q^{C1}(t) = \frac{1-\sum_{i=t1}^{t2-1}(P_i^C\,|P^{C_1})^q}{q-1} \quad ;$$

$$S_q^{C_m}(t) = \frac{1-\sum_{i=t_m}^{L-1}(P_i^C\,|P^{C_m})^q}{q-1} \quad (8)$$

Where $P^{C_0} = \sum_{i=0}^{t-1} P_i^C$; $P^{C_1} = \sum_{i=t}^{t_2-1} P_i^C$; $P^{C_m} = \sum_{i=t_m}^{N-1} P_i^C$

Accommodating the optimal threshold values as:

$$\left[\overrightarrow{t_0^*}.\overrightarrow{t_1^*}.\overrightarrow{t_2^*}.\cdots.\overrightarrow{t_m^*}\right] = \arg\max(S_q^{C_0}(t) + S_q^{C_1}(t) + \cdots + S_q^{C_m}(t) + (1+q)\cdot S_q^{C_0}(t)\cdot S_q^{C_1}(t) \cdots S_q^{C_m}(t)) \quad (9)$$

Subject to the following constraint:

$$|P^{C_0} + P^{C_1}| - 1 < S^{C_0} < 1 - |P^{C_0} + P^{C_1}| \,.\, |P^{C_1} + P^{C_2}| - 1 < S^{C_1} < 1 - |P^{C_1} + P^{C_2}| \,\&\, |P^{C_{m-1}} + P^{C_m}| - 1 < S^{C_{m-1}} < 1 - |P^{C_{m-1}} + P^{C_m}| \quad (10)$$

P^{C_0} , P^{C_1}, ... P^{C_m} can be constructed using the probability distribution of pixel values corresponding to the threshold levels $\overrightarrow{t_0^*}.\overrightarrow{t_1^*}.\overrightarrow{t_2^*}.\cdots.\overrightarrow{t_m^*}$

3.1.4 Hysteresis Method

For automatic edge detection, a common technique is hysteresis thresholding. However, it is still difficult to determine reasonable high and low thresholds without supervision. Traditional low and high-threshold-linking methods can result in noisy edges and miss some evident edges.

The foundation of hysteresis thresholding is the selection of low and high thresholds, followed by an edge-linking procedure to find edges. If the calculated threshold for single thresholding is too low, spurious or noisy edges will be detected. Conversely, if a very high threshold is used, many significant true edges will be missed. To create a final edge map, hysteresis thresholding calculates both high and low thresholds. If the low and high thresholds are appropriately calculated and their thresholded images are processed, it produces much better results than single thresholding[22].

3.1.5 Fuzzy Entropy Method

With fuzzy entropy, a mathematical technique commonly used to deal with ambiguity and uncertainty, threshold values are computed by using membership functions, making borders within regions less confusing than most thresholding methods. According to fuzzy image segmentation, It is critical to calculate the distance between grayscale values and presumptive thresholds based on membership grades. In this sense, fuzzy entropy (FE) is employed for image thresholding. A given gray value's affinity for a given class is stronger the further it is from a given threshold value. One method for detecting breast cancer is the fuzzy entropy threshold approach[23][24].

3.2. Local Threshold

The original image is divided into smaller sub-images for local thresholding, and a threshold is chosen for each of the sub-images. The point-dependent approach or the region-dependent method can be used to determine a region's threshold. The histograms are calculated for each rectangular, overlapping sub-images that make up an image. At least one pixel from the sub-image is an item, and one at least is taken from the Background.

If the sub-image contains a bimodal histogram, the minimum between the peaks should be used as a local threshold. If a histogram is unimodal, the threshold can be calculated by changing the local thresholds found for nearby sub-images. For each pixel, iterative raising is required to obtain the right thresholds. The computational cost of local thresholding is typically higher than that of global thresholding. It is extremely useful for segmentation objects from different backgrounds[25].

3.2.1 Ni-Black Method

Local thresholding algorithms such as Ni-Black modify their thresholds according to the local mean and standard deviation in an area surrounding each pixel position. Images with irregular backgrounds are typically subjected to this local thresholding method. A small window's average illumination value is called the local mean (mean cakulated over a small window), whereas the overall illumination of the image is known as the global mean. Local Thresholding value for Niblack thresholding LT(x,y) at (x,y) is computed as given in Eq (11) [26]:

$LT(x, y) = \mu(x, y) + \lambda * \sigma(x, y)$ (11)

(x, y) is the local mean of the pixel (x, y), and (x, y) is the standard deviation of the pixel in a window of size z*z & λ is a bias set to 0.5. The threshold value is adjusted based on the contrast of the local pixel value. The bias variable λ controls the level of adaptation for different threshold levels[26].

3.2.2 Bernsen Method

A local binarization technique, as proposed by Bernsen, employs local contrast value to establish a local threshold value. The local threshold value for each pixel (x, y) is calculated by the relation (12)[27].

$T(x,y)=(Imax+IMin)/2$ (12)

Imax is the image's maximum gray level value, and IMin is the image's minimum gray level value centred in (x,y). If the grayscale image is not uniform, the threshold assignment can be written as Imax - Imin >L because it is based on local contrast values.

Then

T (x, y) = (Imax + IMin)/2 ElseT(x, y) = GT //(else threshold value is calculated by global thresholding technique.) L is a contrast threshold, and GT is a global threshold value[27].

4. OF Thresholding with Optimization Algorithms

Formally, a metaheuristic is described as guiding a subordinate heuristic by intelligently combining all ideas for exploiting and exploring the search space. Information is organized using learning methods to look for close-to-ideal solutions efficiently. Instead, a metaheuristic is an algorithm typically created to solve approximately a large range of difficult optimization problems without needing to be specifically tailored to each one[30]. There are many algorithms that will be explained as shown below in Figure 2:

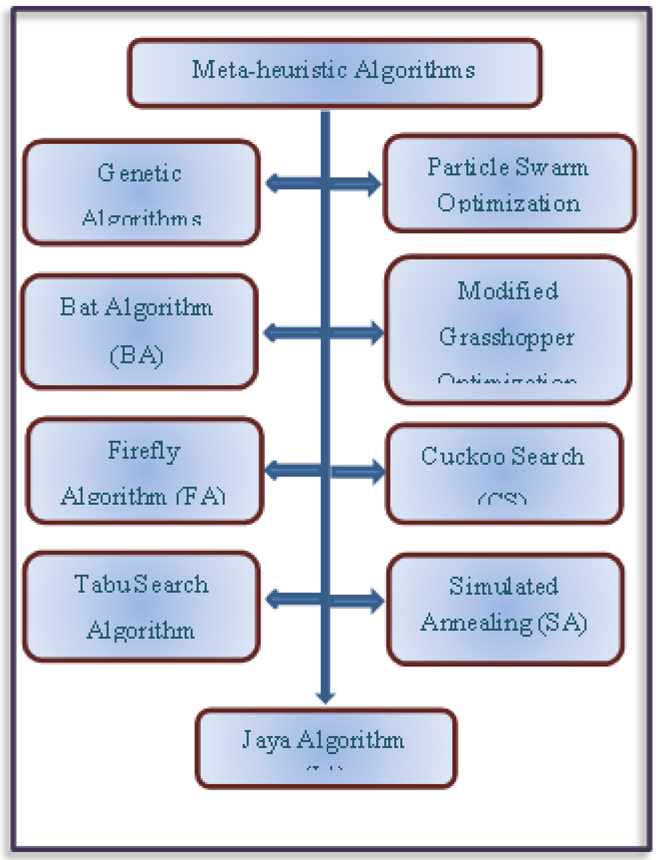

Fig 2: Meta-heuristic Algorithms.

4.1 Genetic Algorithms (GA)

An optimal or extremely close fit function is produced by the natural or genetic selection of aw1 population or potential solutions. Genetic algorithms search for models based on this process[28]. Using a genetic algorithm, (S. Pare et al.) segmented satellite images using multiple objective functions. Three of the most prominent multilevel thresholding functions, Tsallis entropy, between-class variance, and Kapur's entropy, have been used in a genetic algorithm-based multilevel thresholding method for image segmentation. In almost every case, Kapur's entropy-based method performed better in terms of the best threshold values, PSNR, MSE, SSIM, and FSIM. The findings imply that multilevel thresholding can effectively use GA with Kapur's entropy. The proposed technique's validity and accuracy are reported both qualitatively and quantitatively. Consequently, the Kapur's-GA approach is a successful method for identifying optimal threshold values[29]. Also, use GA by hybridizing it with EDA to solve hot problems in cloud computing[30].

4.2 Particle Swarm Optimization (PSO)

PSO is impacted by the social behaviour of living things, such as flocks of birds finding food sources, which is an intelligent evolutionary computing technology. Eberhart and Kennedy introduced it (Kennedy and Eberhart). It is a computational technique that resolves a problem by repeatedly attempting to enhance a candidate arrangement about a certain percentage of value. PSO aims to discover the best answer by working together and sharing data among particles or molecules in a group that may be considered a population. A particle is an element or constituent of the so-called swarm. A swarm must fly over the hunting area to locate promising scene territories. Every particle has a search space across which it looks for food. Each particle is initialized at random and carries both velocity and position information. Each particle is aware of its optimal place inside the group of particles as well Gbest[31].

For example, IQPSO is used in the medical field to segment brain tissue through magnetic resonance images (MRI)[32].

4.3 Bat Algorithm (BA)

BA is a brand-new evolutionary optimization algorithm that searches global optima by relying on individual collaboration. Designing a global search formula and a local search formula are the two difficulties involved in BA structure design. (a) Global search algorithm design The traditional BA's velocity formula states that the current optimal position is the only factor in determining how to position a bat. In this situation, bats can become caught in the local optimum. (b) Design of local search formula Lin et al. suggested a chaotic Levy BA that modified the original local search formula by using chaos functions and the Levy flight formula; according to (S. Pare et al.) an ideal multilevel segmentation algorithm has been put forth that makes use of Renyi's entropy function and the Bat algorithm to get the best threshold values for segmenting color images. The bat algorithm has been utilized for multilevel threshold-based color image segmentation, such as satellite image processing [33].

4.4 Modified Grasshopper Optimization Algorithm (GOA)

In recent years, the Grasshopper Optimization Algorithm (GOA) has been inspired by the foraging and swarming behaviour of grasshoppers in nature to develop a swarm intelligence system. A wide variety of optimization problems in various fields have been effectively solved using the GOA algorithm. A grasshopper is an insect notorious for being a pest that interferes with and harms crops and agriculture. Nymph and maturity are two phases in their life cycle. The nymphal phase consists of small, deliberate movements, whereas the adult phase consists of sudden, long-distance moves. The nymphal and adult phases represent the intensification and diversification phases of GOA[18]. In this search field, metaheuristic algorithms are used to find the optimal thresholds. (HONGNAN LIANG et al) The multilevel image segmentation problem was solved using the Grasshopper optimization algorithm. Many other uses exist for higher segmentation accuracy and fewer iterations[34].

4.5 Firefly Algorithm (FA)

Each firefly (population member) stands for a potential solution in the search space. Fireflies search for suitable candidates for solutions by moving into other positions. The radiated light's intensity, often evaluated by the fitness value, determines the attractiveness[35]. Utilized the three idealized rules below to describe our Firefly Algorithm (FA) simply: Because all fireflies are unisex and are therefore attracted to other fireflies regardless of gender, and because attractiveness is inversely correlated with brightness, the less attractive of any two flashing fireflies will gravitate toward the more attractive one. Both the appeal and the brightness decline as the distance between them rises. The movement of a firefly depends on whether there is a brighter one randomly; The brightness of the objective function affects or determines a firefly's luminosity(Abhay Sharma et al.) employed the Firefly algorithm to segment grayscale images effectively. To improve the process's effectiveness, an optimal searching technique can be applied. Because of its high conversion rate and quick processing, the Firefly algorithm is one of the best for segmenting images. Firefly with Levy flying was used to optimize both parameters while considering computation time and the maximum entropy objective function. Comparing the proposed method to other methods, they are far more time- and resource-efficient [36].

4.6 Cuckoo Search (CS)

The cuckoo search algorithm was created using cuckoo bird reproduction as inspiration. Cuckoo search is extensively utilized to resolve optimization problems in various technical domains. However, because CS employs a unitary search strategy, which makes it simple for the algorithm to get trapped in the local optimum and enter an early convergence state, all cuckoos exhibit comparable search behaviour. Because it uses a switching parameter to balance local and global random walks, it is very effective at solving global optimization[37]. (S. Pare et al.) used the cuckoo search algorithm in an effective multilevel thresholding technique to make the multilevel cross-minimum entropy more usable and reduce the complexity, choose the optimal threshold values more quickly and precisely than other comparable techniques, and produce high-quality segmented images[38].

4.7 Tabu Search Algorithm(TSA)

Like other metaheuristic algorithms, TSA begins with a viable space initial solution. Then, among the neighbors of the current solution, it selects the best neighbor's response. The algorithm then keeps track of the best non-tabu solution in the immediate area; if not, it checks the aspiration criterion. Even if the neighbor's response is on the tabu list, it advances to the new best if it meets the ambition condition and has a higher fitness value than the current best. The tabu list is updated as the algorithm switches between solutions. This entails adding the probable solution to the tabu list to avoid cycles and constantly accessing a certain set of solutions. TSA uses the tabu list as a means of eluding the local optimal. Some elements will become expendable after the preceding move is added to the tabu list. A tabu time parameter determines the time that a movement remains in the tabu list. Until a stopping requirement is met, there is a constant movement from one potential solution to another in the neighborhood [39]. In the medical field, (Diptoneel Kayal and Sreeparna Banerjee) employed a dynamic threshold with Tabu Search to find solid exudate in the image of the retina. Diabetic retinopathy is a retinal disease that affects people with diabetes and can cause blindness[40].

4.8 Simulated Annealing(SA)

A physical annealing process is used as a model for the SA heuristic, which involves cooling solids until their atoms are relocated to form low-energy crystals. The basic elements of the method were first defined by Metropolis et al. in 1953, and Kirkpatrick et al. first provided the whole algorithm, also suggesting the algorithm as a combinatorial optimization tool to minimize a cost function in combinatorial problems. The algorithm eventually converges to a better local minimum by accepting both solutions that increase the cost function and modified ones that decrease it. After starting with a random solution, the algorithm uses 95, a perturbation method, to generate a neighboring solution by altering the present solution slightly (simulating that atoms move randomly within the solid). If the new solution's quality (energy), defined by the cost function, is lower, the algorithm prefers it to the preceding one. Without such a condition, the solution is likely to be accepted as e E/T, where E denotes the energy switch between solutions and T their temperature. Using temperature as the control parameter, the algorithm gradually reduces the temperature until a minimum temperature is reached after the solutions have been disturbed sufficiently to allow a thermal equilibrium. In implementing the SA algorithm, two types of choices must be considered: problem-specific and generic. It is a problem-specific choice to implement the number of simulated annealing functions, such as cost function, perturbation method, and solution structure, based on the problem of interest. A SA algorithm's specific problem is not related to the setting of cooling parameters[41].

4.9 Jaya Algorithm(JA)

To solve constrained and unconstrained optimization problems, Rao created a revolutionary swarm-based heuristic, the Jaya algorithm. Jaya means victory in Sanskrit. Using this approach, the searching agents or particles continuously strive to avoid the worst solution (i.e., failures) in each iteration, coming closer to the target (i.e., victory). Due to upgrading all JA candidates in each iteration, all solutions produced by iteration are better than the preceding worst solution. The seeking agent adjusts its position essentially by preserving only the best position and ignoring all worse positions. Every proposed solution or searching agent in JA is known as a particle (X (j.k.i)). Every particle in the search region seeks the most effective solution (J Best) of the goal or cost function(J) and avoids the worst solution (J Worst). The JA flowchart is depicted. This is accomplished by optimizing the objective function (J), assuming 'n' candidates (i.e., k = 1, 2,..., n) and design variables or generators (i.e., j = 1, 2,..., m). The positions of the particles are mathematically updated as (13)[42]:

$$\acute{X}_{j.k.i} = X_{j.k.i} + r_{1.j.i}\left(X_{j.best.i} - \left|X_{j.k.i}\right|\right) - r_{2.j.i}\left(X_{j.worst.i} - \left|X_{j.k.i}\right|\right) \quad (13)$$

During iteration, X (j.k.i) represents the jth variable for the kth candidate. The random numbers r (1. j.i) and r (2. j.i) have values ranging from 0 to 1. The greatest and worst candidate values are X (j.best.i) and X (j.worst.i), respectively. X (j.k.i) now has a new value (j.k.i). If X (j.k.i) produces the highest fitness value compared to X_, it is kept (j.k.i). At the end of each iteration, the cost function values are kept, and the next iteration takes these values as input for computation until the optimal solution is reached [43].

5. Conclusion

The segmentation of images is one of the significant applications of metaheuristic algorithms. Pattern recognition and image analysis both heavily rely on image segmentation. Image segmentation is a method or procedure for dividing digital images into various groups of pixels. Most image analysis, object representation, and visualization algorithms include image thresholding as an initial step. In this paper, a set of previous threshold studies are reviewed. In addition, the threshold methods used for image segmentation were mentioned, which include two types of methods, global methods and local methods, each of which has different types. Threshold optimization algorithms are also included, and these algorithms are explained in detail.

6. References

[1] T. Y. Goh, S. N. Basah, H. Yazid, M. J. Aziz Safar, and F. S. Ahmad Saad, "Performance analysis of image thresholding: Otsu technique," *Meas. J. Int. Meas. Confed.*, vol. 114, pp. 298–307, Jan. 2018, doi: 10.1016/j. measurement. 2017.09.052.

[2] M. Azarbad, A. Ebrahimzade, and V. Izadian, "Segmentation of Infrared Images and Objectives Detection Using Maximum Entropy Method Based on the Bee Algorithm." [Online]. Available: http://www.mirlabs.org/ijcisim.

[3] S. Aja-Fernández, A. H. Curiale, and G. Vegas-Sánchez-Ferrero, "A local fuzzy thresholding methodology for multiregion image segmentation," *Knowledge-Based Syst.*, vol. 83, no. 1, pp. 1–12, 2015, doi: 10.1016/j.knosys.2015.02.029.

[4] K. Tang, X. Yuan, T. Sun, J. Yang, and S. Gao, "An improved scheme for minimum cross entropy threshold selection based on genetic algorithm," *Knowledge-Based Syst.*, vol. 24, no. 8, pp. 1131–1138, 2011, doi: 10.1016/j.knosys.2011.02.013.

[5] D. Mishra, I. Bose, U. C. De, and M. Das, "Medical Image Thresholding Using Particle Swarm Optimization," in *Advances in Intelligent Systems and Computing*, 2015, vol. 308 AISC, no. VOLUME 1, pp. 379–383, doi: 10.1007/978-81-322-2012-1_39.

[6] A. K. Bhandari, A. Kumar, S. Chaudhary, and G. K. Singh, "A novel color image multilevel thresholding based segmentation using nature inspired optimization algorithms," *Expert Syst. Appl.*, vol. 63, pp. 112–133, Nov. 2016, doi: 10.1016/j.eswa.2016.06.044.

[7] M. A. El Aziz, A. A. Ewees, and A. E. Hassanien, "Whale Optimization Algorithm and Moth-Flame Optimization for multilevel thresholding image segmentation," *Expert Syst. Appl.*, vol. 83, pp. 242–256, Oct. 2017, doi: 10.1016/j.eswa.2017.04.023.

[8] A. Ahilan *et al.*, "Segmentation by Fractional Order Darwinian Particle Swarm Optimization Based Multilevel Thresholding and Improved Lossless Prediction Based Compression Algorithm for Medical Images," *IEEE Access*, vol. 7, pp. 89570–89580, 2019, doi: 10.1109/ACCESS.2019.2891632.

[9] A. Ramya, D. Murugan, G. Murugeswari, and N. Joseph, "Adaptive multi-threshold based de-noising filter for medical image applications," 2019.

[10] G. Ding, F. Dong, and H. Zou, "Fruit fly optimization algorithm based on a hybrid adaptive-cooperative learning and its application in multilevel image thresholding," *Appl. Soft Comput. J.*, vol. 84, p. 105704, 2019, doi: 10.1016/j.asoc.2019.105704.

[11] W. Liu *et al.*, "Renyi's entropy based multilevel thresholding using a novel meta-heuristics algorithm," *Appl. Sci.*, vol. 10, no. 9, 2020, doi: 10.3390/app10093225.

[12] S. Wang, K. Sun, W. Zhang, and H. Jia, "Multilevel thresholding using a modified ant lion optimizer with opposition-based learning for color image segmentation," *Math. Biosci. Eng.*, vol. 18, no. 4, pp. 3092–3143, 2021, doi: 10.3934/mbe.2021155.

[13] L. He and S. Huang, "An efficient krill herd algorithm for color image multilevel thresholding segmentation problem," *Appl. Soft Comput. J.*, vol. 89, p. 106063, 2020, doi: 10.1016/j.asoc.2020.106063.

[14] F. Rezaei, H. Izadi, H. Memarian, and M. Baniassadi, "The effectiveness of different thresholding techniques in segmenting micro CT images of porous carbonates to estimate porosity," *J. Pet. Sci. Eng.*, vol. 177, pp. 518–527, 2019, doi: 10.1016/j.petrol.2018.12.063.

[15] Z. Wang, E. Wang, and Y. Zhu, "Image segmentation evaluation: a survey of methods," *Artif. Intell. Rev.*, vol. 53, no. 8, pp. 5637–5674, Dec. 2020, doi: 10.1007/s10462-020-09830-9.

[16] S. J. Mousavirad and H. Ebrahimpour-Komleh, "Human mental search-based multilevel thresholding for image segmentation," *Appl. Soft Comput.*, vol. 97, Dec. 2020, doi: 10.1016/j.asoc.2019.04.002.

[17] J. Rahaman and M. Sing, "An efficient multilevel thresholding based satellite image segmentation approach using a new adaptive cuckoo search algorithm," *Expert Syst. Appl.*, vol. 174, no. January, p. 114633, 2021, doi: 10.1016/j.eswa.2021.114633.

[18] Y. Meraihi, A. B. Gabis, S. Mirjalili, and A. Ramdane-Cherif, "Grasshopper optimization algorithm: Theory, variants, and applications," *IEEE Access*, vol. 9, pp. 50001–50024, 2021, doi: 10.1109/ACCESS.2021.3067597.

[19] X. Bao, H. Jia, and C. Lang, "A Novel Hybrid Harris Hawks Optimization for Color Image Multilevel Thresholding Segmentation," *IEEE Access*, vol. 7, pp. 76529–76546, 2019, doi: 10.1109/ACCESS.2019.2921545.

[20] V. Rajinikanth, N. Dey, S. C. Satapathy, and A. S. Ashour, "An approach to examine Magnetic Resonance Angiography based on Tsallis entropy and deformable snake model," *Futur. Gener. Comput. Syst.*, vol. 85, pp. 160–172, 2018, doi: 10.1016/j.future.2018.03.025.

[21] A. K. Bhandari, *A novel beta differential evolution algorithm-based fast multilevel thresholding for color image segmentation*, vol. 32, no. 9. Springer London, 2020.

[22] S. Khan, D. H. Lee, M. A. Khan, A. R. Gilal, J. Iqbal, and A. Waqas, "Efficient and improved edge detection via a hysteresis thresholding method," *Curr. Sci.*, vol. 118, no. 6, pp. 954–960, 2020, doi: 10.18520/cs/v118/i6/954-960.

[23] K. G. Dhal, S. Ray, A. Das, J. Gálvez, and S. Das, "Fuzzy Multilevel Color Satellite Image Segmentation Using Nature-Inspired Optimizers: A Comparative Study," *J. Indian Soc. Remote Sens.*, vol. 47, no. 8, pp. 1391–1415, 2019, doi: 10.1007/s12524-019-01005-6.

[24] X. Li, Z. Zhao, and H. D. Cheng, "Fuzzy Entropy Threshold Approach to Breast Cancer Detection."

[25] H. Al-Hashimy, "Using Threshold Methods to Segment Highly Images beans without overlapping Saba Q."

[26] S. Khairnar, S. D. Thepade, and S. Gite, "Effect of

image binarization thresholds on breast cancer identification in mammography images using OTSU, Niblack, Burnsen, Thepade's SBTC," *Intell. Syst. with Appl.*, vol. 10–11, p. 200046, 2021, doi: 10.1016/j.iswa.2021.200046.

[27] S. N and V. S, "Image Segmentation By Using Thresholding Techniques For Medical Images," *Comput. Sci. Eng. An Int. J.*, vol. 6, no. 1, pp. 1–13, 2016, doi: 10.5121/cseij.2016.6101.

[28] J. M. García, C. A. Acosta, and M. J. Mesa, "Genetic algorithms for mathematical optimization," *J. Phys. Conf. Ser.*, vol. 1448, no. 1, 2020, doi: 10.1088/1742-6596/1448/1/012020.

[29] S. Pare, A. K. Bhandari, A. Kumar, G. K. Singh, and S. Khare, "Satellite image segmentation based on different objective functions using genetic algorithm: A comparative study," *Int. Conf. Digit. Signal Process. DSP*, vol. 2015-Septe, no. 1, pp. 730–734, 2015, doi: 10.1109/ICDSP.2015.7251972.

[30] S. Pang, W. Li, H. He, Z. Shan, and X. Wang, "An EDA-GA Hybrid Algorithm for Multi-Objective Task Scheduling in Cloud Computing," *IEEE Access*, vol. 7, pp. 146379–146389, 2019, doi: 10.1109/ACCESS.2019.2946216.

[31] A. Pradhan, S. K. Bisoy, and A. Das, "A survey on PSO based meta-heuristic scheduling mechanism in cloud computing environment," *Journal of King Saud University - Computer and Information Sciences*. King Saud bin Abdulaziz University, 2021, doi: 10.1016/j.jksuci.2021.01.003.

[32] R. Radha and R. Gopalakrishnan, "A medical analytical system using intelligent fuzzy level set brain image segmentation based on improved quantum particle swarm optimization," *Microprocess. Microsyst.*, vol. 79, Nov. 2020, doi: 10.1016/j.micpro.2020.103283.

[33] S. Pare, A. K. Bhandari, A. Kumar, and G. K. Singh, *Rényi's entropy and bat algorithm based color image multilevel thresholding*, vol. 748. Springer Singapore, 2019.

[34] H. Liang, H. Jia, Z. Xing, J. Ma, and X. Peng, "Modified grasshopper algorithm-based multilevel thresholding for color image segmentation," *IEEE Access*, vol. 7, pp. 11258–11295, 2019, doi: 10.1109/ACCESS.2019.2891673.

[35] H. Wang *et al.*, "Firefly algorithm with neighborhood attraction," *Inf. Sci. (Ny).*, vol. 382–383, pp. 374–387, 2017, doi: 10.1016/j.ins.2016.12.024.

[36] A. Sharma, R. Chaturvedi, U. K. Dwivedi, S. Kumar, and S. Reddy, "Firefly algorithm based effective gray scale image segmentation using multilevel thresholding and entropy function," *Int. J. Pure Appl. Math.*, vol. 118, no. 5 Special Issue, pp. 437–443, 2018.

[37] H. Peng, Z. Zeng, C. Deng, and Z. Wu, "Multi-strategy serial cuckoo search algorithm for global optimization," *Knowledge-Based Syst.*, vol. 214, p. 106729, 2021, doi: 10.1016/j.knosys.2020.106729.

[38] S. Pare, A. Kumar, V. Bajaj, and G. K. Singh, "An efficient method for multilevel color image thresholding using cuckoo search algorithm based on minimum cross entropy," *Appl. Soft Comput. J.*, vol. 61, pp. 570–592, Dec. 2017, doi: 10.1016/j.asoc.2017.08.039.

[39] A. Bagheri, M. Bagheri, and A. Lorestani, "Optimal reconfiguration and DG integration in distribution networks considering switching actions costs using tabu search algorithm," *J. Ambient Intell. Humaniz. Comput.*, 2020, doi: 10.1007/s12652-020-02511-z.

[40] G. Sangeetha, M. Vijayalakshmi, S. Ganapathy, and A. Kannan, *A heuristic path search for congestion control in WSN*, vol. 11. 2018.

[41] J. Lee and D. Perkins, "A simulated annealing algorithm with a dual perturbation method for clustering," *Pattern Recognit.*, vol. 112, p. 107713, 2021, doi: 10.1016/j.patcog.2020.107713.

[42] E. H. Houssein, A. G. Gad, and Y. M. Wazery, "Jaya Algorithm and Applications: A Comprehensive Review," in *Lecture Notes in Electrical Engineering*, vol. 696, Springer Science and Business Media Deutschland GmbH, 2021, pp. 3–24.

[43] E. H. Houssein, A. G. Gad, and Y. M. Wazery, *Jaya Algorithm and Applications: A Comprehensive Review*, vol. 696. Springer International Publishing, 2021.

طرق التحسين لعتبة الصورة: مراجعة

بشرى علي عبد،عزمي توفيق حسين ،اثير باسل عبد الكريم

قسم علوم الحاسبات ،كلية علوم الحاسبات وتكنولوجيا المعلومات ، جامعة الانبار
bus20c1004@uoanbar.edu.iq

الخلاصة:

يعد تعيين حد بمستوى رمادي مناسب في معالجة الصور لفصل الكائنات عن خلفياتها أمرًا بالغ الأهمية. واحدة من أبسط الطرق وأكثرها شيوعًا لتقسيم الصور هي العتبة القائمة على المدرج التكراري. العتبة هي تقنية شائعة لتجزئة الصور بسبب بساطتها. يتم استخدام العتبة لفصل خلفية الصورة عن المقدمة. هناك العديد من طرق العتبة. تهدف هذه الورقة إلى مراجعة العديد من الدراسات السابقة وذكر أنواع العتبة. وهي تشتمل على نوعين: طرق العتبة العمومية والمحلية ، ويشتمل كل نوع على مجموعة من الأساليب. تتضمن طريقة العتبة الشاملة (طريقة أوتسو ، طريقة كابور للإنتروبيا ، طريقة تساليس للإنتروبيا ، طريقة التخلفية وطريقة الانتروبيا الضبابي)، وتشمل طريقة العتبة المحلية (طريقة ني–بلاك وطريقة بيرسن). يتم أيضًا توضيح خوارزميات التحسين (الخوارزمية الجينية، وتحسين حشد الجسيمات، وخوارزمية الخفافيش، وتحسين الجندب المعدل، وخوارزمية Firefly، و Cuckoo Search، وخوارزمية Tabu Search ، والتليين المحاكي، وخوارزمية Jaya) المستخدمة جنبًا إلى جنب مع طرق العتبة.