Automation, Control and Intelligent Systems
2024, Vol. 12, No. 3, pp. 60-70
https://doi.org/10.11648/j.acis.20241203.12

Research Article

Image Multi-threshold Segmentation Based on an Ameliorated Harmony Search Optimization Algorithm

Xiuteng Shu, Xiangmeng Tang*

School of Information Science and Electrical Engineering, Shandong Jiaotong University, Jinan, China

Abstract

Image segmentation is the basis and premise of image processing, though traditional multi-threshold image segmentation methods are simple and effective, they suffer the problems of low accuracy and slow convergence rate. For that reason, this paper introduces the multi-threshold image segmentation scheme by combining the harmony search (HS) optimization algorithm and the maximum between-class variance (Otsu) to solve them. Firstly, to further improve the performance of the basic HS, an ameliorated harmony search (AHS) is put forward by modifying the generation method of the new harmony improvisation and introducing a convergence coefficient. Secondly, the AHS algorithm, which takes the maximum between-class variance as its objective function, namely AHS-Otsu, is applied to image multi-level threshold segmentation. Finally, six test images are selected to verify the multilevel segmentation performance of AHS-Otsu. Peak signal-to-noise ratio (PSNR) and structural similarity index (SSIM) are two commonly used metrics for evaluating the effectiveness of image segmentation, which are both used in this article. Comprehensive experimental results indicate that the AHS-Otsu does not only has fast segmentation processing speed, but also can obtain more accurate segmentation performance than others, which prove the effectiveness and potential of the AHS-Otsu algorithm in the field of image segmentation especially for the multi-threshold.

Keywords

Image Segmentation, Harmony Search, Otsu, Multi-threshold

1. Introduction

In this era of rapid development of artificial intelligence, computer vision takes an important role. As the basis and premise technology of computer vision, image segmentation is a crucial step from image processing to image analysis, and greatly affects the final application [1]. By segmentation, the image can be divided into non-overlapping areas so that the same region shares the similar visual features, and vice versa. This will facilitate the depiction, characterization, and visualization of the area of interest [2, 3].

At present, the image segmentation techniques can be divided into four categories: region-based segmentation, edge-based segmentation, threshold-based segmentation, and histogram-based segmentation [4]. Each approach has its own pros and cons, so it is important to choose the appropriate image segmentation technique in practical application. As for the threshold-based segmentation, this is the most widely used scheme due to its simplicity, high efficiency and good segmentation effect. The core of threshold-based segmentation is to determine the threshold, since the suitable threshold can get more accurate image segmentation results [5].

*Corresponding author: txm12332@163.com (Xiangmeng Tang)

Received: 25 June 2024; **Accepted:** 20 August 2024; **Published:** 27 August 2024

As a famous global threshold segmentation method, Otsu also known as maximum between-class variance, which was proposed in 1979 and it has been used for image binary segmentation [6]. The principle is that the variance between the foreground and the background is the largest after the image is segmented by the obtained threshold. The image distribution uniformity can be expressed by variance, and the higher value of it, the more obvious the difference between background and foreground [7]. Though Otsu algorithm is easy to operate, it is only suitable for single threshold segmentation. However, when the between-class variance function of the image histogram showing multimodal, Otsu is hard to get good application due to its exponential increase in time-consuming for multi-threshold segmentation [8].

With the purpose of speed up the image multilevel threshold segmentation, scholars have considered the Otsu's segmentation is modeled as the optimization algorithms problem. In the research of Banerjee S et al., the author combined the Otsu and the improved ACO for multi-threshold segmentation [9] Huang C et al. proposed an Otsu image segmentation based on fruitily optimization algorithm [10]. In the research of Pare, S, et al., the technique of multilevel image thresholding using strongest schema learning GA optimization was presented [11]. The application of PSO and ABC algorithms in multi-threshold segmentation was studied by the research of Shu-Liang W et al. [12]. Modified BF algorithm was also adopted in multilevel thresholding for image segmentation in the research of Sathya P D et al. [13]. Though experimental results show that their proposed methods provided faster segmentation speed compared with the original Otsu, the image segmentation performance was still limited.

As a relatively new optimization algorithm, Harmony Search (HS) was proposed by Geem etc. in 2001. It is simple, efficient and gradually becoming one of the popular meta-heuristic algorithms [14]. However, compared with some other well-known optimization methods, the accuracy and stability of the basic HS are relatively weak. Though many HS variants have been proposed during the past time, the performance still needs to be improved. This article proposes an ameliorated harmony search, namely AHS, to further enhance the optimization accuracy along with the stability. On this foundation, an image segmentation method based on AHS is formed by effectively combining the ideas of AHS and Otsu, namely AHS-Otsu. The new approach can obtain the optimal multilevel segmentation threshold quickly, accurately, and stable, to achieve better segmentation effects.

The structure of this paper is as follows: Section 2 describes the Otsu concept and the basic HS algorithm. In Section 3, the proposed AHS is presented. Section 4 gives a comprehensive comparison to prove the effectiveness of the image segmentation based on AHS-Otsu. Conclusions are displayed in Section 5.

2. Basic Introduction of the Related Methods

2.1. Review of the Otsu Concept

Image segmentation is used to distinguish and extract meaningful objects. As one of important image threshold tools, the Otsu method based on between-class variance has simple principle, relatively good segmentation effect and strong adaptability. It employs the image histogram calculation to find the largest between-class variance value over the entire grayscale traversal, thereby determining the best threshold.

The original Otsu is mainly used for image binary segmentation. However, researches show that multi- thresholding has better segmentation effects in many occasions. In view of the Otsu's basic concept, the criterion of multilevel segmentation is to maximize the objective function with the selected thresholds as parameters. Here, for a given image, the gray level range is set to: $\{0,1,2,\dots,(L-1)\}$. If the image is considered to be divided into m regions, so (m-1) appropriate thresholds should be chosen to partition the solution space.

Assume that the (m-1) thresholds are $k_1, k_2, \dots, k_{m-1}$, then the distribution of the multiple segmentation regions obtained is: $R_0 = \{0,1,2,\dots,k_1\}$, $R_1 = \{k_1+1, k_1+2,\dots,k_2\}$,..., $R_{m-1} = \{k_{m-1}+1, k_{m-1}+2,\dots,L-1\}$.

If the number of pixel i is n_i, so the amount of pixels in the whole image is $N = \sum_{i=0}^{L-1} n_i$. Meanwhile, the proportion of the pixel with level i is $p_i = n_i / N$. Then the percentage of pixels in each partition of the image can be calculated as: $w_0 = \sum_{i=0}^{k_1} p_i$, $w_1 = \sum_{i=k_1+1}^{k_2} p_i$, …, $w_{m-1} = \sum_{i=k_{m-1}+1}^{L-1} p_i$.

The mean value of each partition is: $\mu_0 = \frac{\sum_{i=0}^{k_1} i \times p_i}{w_0}$, $\mu_1 = \frac{\sum_{i=k_1+1}^{k_2} i \times p_i}{w_1}$,…, $\mu_{m-1} = \frac{\sum_{i=k_{m-1}+1}^{L-1} i \times p_i}{w_{m-1}}$, and the whole mean value of the image is $\mu = \sum_{i=0}^{L-1} w_i \times \mu_i$.

So, the optimal segmentation thresholds are obtained by maximizing the following equation:

$$\text{Maximize} \quad f(t) = \sum_{i=0}^{m-1} w_i (\mu_i - \mu)^2 \tag{1}$$

2.2. The Basic HS Algorithm

Harmony search (HS) is a music-inspired optimization algorithm, which searches for the global solution based on an objective function. The strategy of HS is similar to that of musicians looking for harmonic tones based on an aural aesthetic criterion [15, 16]. It is simple but with efficient memory-based stochastic search technique. According to the author's statement, the entire operation of basic HS can be divided into five steps.

Step 1: Parameters initialization and provide the optimization requirement. Typically, the objective function $f(x)$ which needs to be maximized (or minimized), and x is a candidate solution consisting of N decision variables $x_i \in [x_L, x_U]$, x_L and x_U are the limiting boundaries. The initialization parameter settings include *HMS*, *HMCR*, *PAR*, *bw* and *NI*. All the above parameters are set manually.

Step 2: Initialization of the harmony memory (*HM*). For HS, the initial solutions are obtained by $x_i^j = x_L + rand \times (x_U - x_L)$, in which the value of j is from 1 to *HMS* and *rand* is a random number between 0 and 1. These harmony vectors are stored in *HM*.

Step 3: Improvisation of a new harmony. The new harmony vector can be expressed as $x_i^{new} = (x_1^{new}, x_2^{new}, \ldots, x_N^{new})$, which is obtained under the collaboration of parameters *HMCR*, *PAR* and *bw*. If operation meets the condition of *HMCR*, the new decision variables will be obtained based on the vectors that stored in *HM*, otherwise they are got by randomly selecting from the whole dataset. When operating under *HMCR*, if the value of judgement is less than *PAR*, the parameter *bw* will be used for the x_i^{new}, i.e. $x_i^{new} = x_i^{new} \pm rand \times bw$.

Step 4: Updating the *HM*. if the generated new harmony vector performs better than the worst harmony in *HM*, it will be stored in *HM* as a replacement. Otherwise, this operation can be skipped.

Step 5: Determine whether the termination requirements are met. Step 3 and Step 4 are executed circularly until the termination criteria are satisfied.

3. The Proposed Ameliorated Harmony Search (AHS) Algorithm

Though the basic HS algorithm is simple operation and efficient, the accuracy of it is relatively unpleasant, and accompanied by the problem of insufficient stability [17]. By analysis of the original HS algorithm and its previous variants, proposes an ameliorated harmony search here, namely AHS, which can make the optimization results more accurate, as well as upgrade the stability and robustness.

3.1. Improvement of the Harmony Improvisation

The pitch adjustment in HS directly affects the accuracy of the algorithm. However, for most HS methods, pitch parameter owns the critical impact. But experiments show that the effects of pitch parameter improvement are getting weaker. In some optimization areas, the convergence factor plays a high impact on the algorithm, thus the concept of convergence coefficient is introduced in HS. To improve the ability of diversity search and avoid local optima, the HS still relies on the pitch parameter's adjustment. While during the later iteration optimization, the proposed convergence coefficient needs to helpful in numerical accuracy. Based on the above analysis, the value of the convergence coefficient β will be expressed as:

$$\beta = \begin{cases} 1, & gn \le \left(\frac{2}{3} \times NI\right) \\ rand, & gn > \left(\frac{2}{3} \times NI\right) \end{cases} \tag{2}$$

where gn is the current generation number and NI is the maximum iterations, and $rand \in [0,1]$.

According to Eq. (2), with the iterative optimization, the value of the convergence coefficient changes from 1 to a random number. Therefore, the generation method of new harmony variables becomes:

$$x_i^{new} = \beta \times x_i^{new\text{-}1} \tag{3}$$

Moreover, the harmony improvisation strategy is also modified by the inspiration of another two well-known optimization algorithms, namely PSO and DE. A new pitch parameter formed by the distance difference between four randomly selected harmony variables from *HM*, combined with the current global optimal variables can create the new harmony vector:

$$x_i^{new} = \frac{gn}{NI} \times x_i^{new\text{-}1} + \left(1 - \frac{gn}{NI}\right) \times x_i^{best} \pm rand \times \left(x_i^1 - x_i^2 + x_i^3 - x_i^4\right) \tag{4}$$

where x_i^{best} is the i-th variable in the current optimal vector, x^1, x^2, x^3, x^4 are the different harmony vectors randomly chosen from the *HM*.

Therefore, by combining Eq. (2) to Eq. (4), the formula of harmony improvisation is:

$$x_i^{new} = \beta \times x_i^{new\text{-}1} = \begin{cases} \frac{gn}{NI} \times x_i^{new\text{-}1} + (1 - \frac{gn}{NI}) \times x_i^{best} \pm rand \times \left(x_i^1 - x_i^2 + x_i^3 - x_i^4\right), & gn \le \left(\frac{2}{3} \times NI\right) \\ rand \times \left[\frac{gn}{NI} \times x_i^{new\text{-}1} + (1 - \frac{gn}{NI}) \times x_i^{best} \pm rand \times \left(x_i^1 - x_i^2 + x_i^3 - x_i^4\right)\right], & gn > \left(\frac{2}{3} \times NI\right) \end{cases} \quad (5)$$

As can be seen from Eq. (5), the superiority of this scheme is that it doesn't need to manually preset the value of the pitch parameter *bw*, so it can be adapted to any situation.

3.2. The Working Procedure of AHS

For the sake of improve the convergence rate and accuracy of the optimization algorithm, the variables of the best harmony will be got more consideration in the AHS. Then, the way of variables selection under the probability of *HMCR* is changed as:

$$x_i^{new} = x_i^{best} \quad (6)$$

where x^{best} is the best performing harmony vector which stored in *HM*.

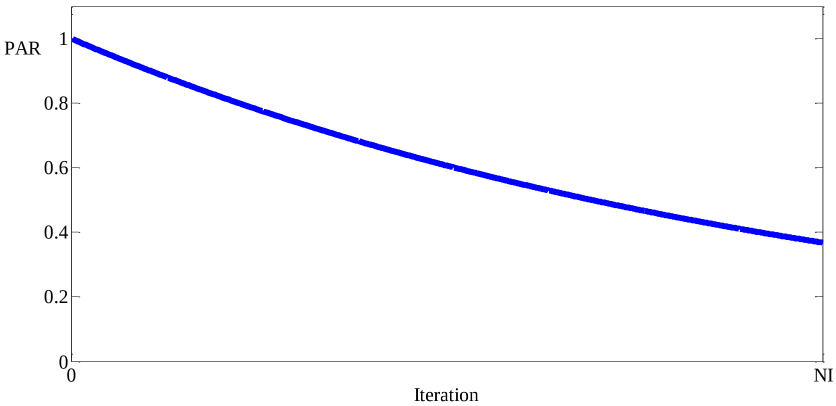

Figure 1. *Variation of PAR versus iteration number.*

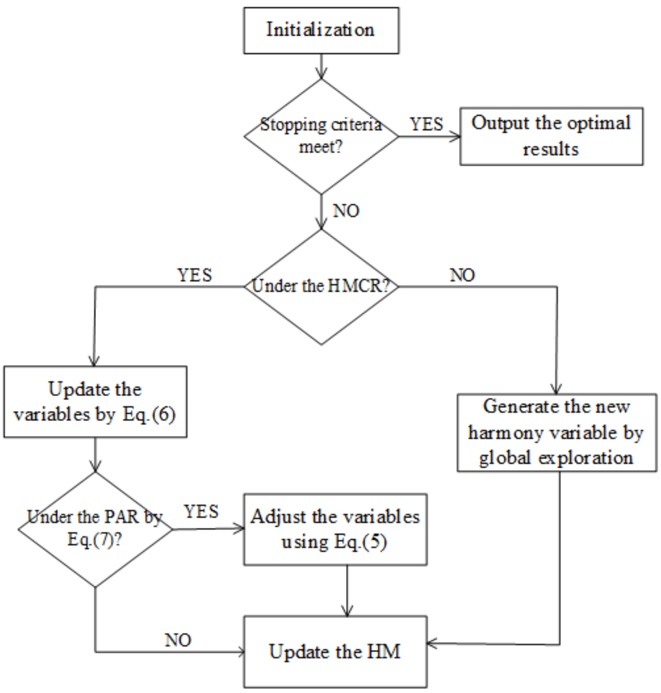

Figure 2. *Flowchart of the AHS optimization algorithm.*

Besides, as mentioned above, in the early iteration stage, the new pitch format has the ability of search diversity. Therefore, the value of the parameter *PAR* used to control the probability of this operation could be relatively higher. However, for the later iteration stage, by reducing the value of *PAR*, more variables can be adjusted to the current optimal state, which will improve the optimization platform and in turn help to further optimization level. For AHS, the parameter *PAR* is set to an exponential mode that its value decreases gradually, namely:

$$PAR = \exp\left(-\frac{gn}{NI}\right) \tag{7}$$

where *NI* is the maximum value of iterations; gn is the current generation number. The numerical variation curve of *PAR* is shown in Figure 1.

In summary, the flow chart of the entire working process of AHS can be seen in Figure 2.

4. Comparison Experiments

To test the application effects of the raised multi-threshold image method, namely AHS-Otsu, which combing the concept of Otsu and the AHS algorithm. Six images (I1~I6) from the BSDS300 image segmentation test set are selected, and the image details are shown in Figure 3.

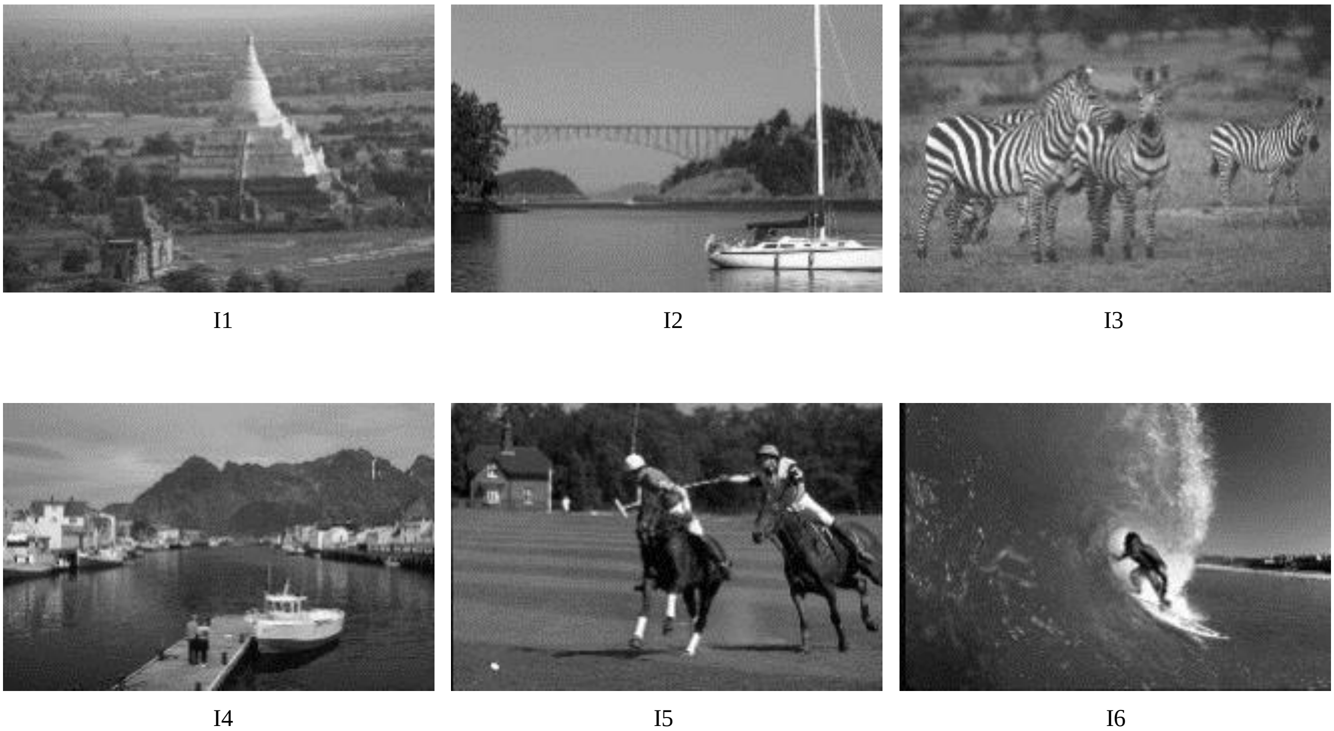

Figure 3. *Test image dataset.*

The peak signal-to-noise ratio (PSNR) and the structural similarity index (SSIM) are two popular metrics for measuring image segmentation performance.

PSNR can be represented by the difference between the original signal and the reconstructed signal, the larger value of it, the better the image segmentation effect. The computing formula of PSNR is:

$$PSNR = 10\lg\left(\frac{V_{\max}^2}{EMS}\right) \tag{8}$$

where $V_{\max}$ indicates the maximum grayscale value of the image; EMS imply the mean square error, that is:

$$EMS = \frac{1}{mn}\sum_{i=0}^{m-1}\sum_{j=0}^{n-1}\left\| I(i,j) - K(i,j) \right\| \tag{9}$$

where *m* and *n* stand for the length and width of the image, respectively; *I* means the original image and *K* is the segmented image.

As another indicator, SSIM represents the similarity between two images, and the numerical of it is between 0 and 1. The higher value of SSIM, the better the image segmentation effect. The calculation of SSIM is:

$$SSIM = \frac{2\mu_x\mu_y + C_a}{\mu_x^2 + \mu_y^2 - C_a} \times \frac{2\delta_{xy} + C_b}{\delta_x^2 + \delta_y^2 + C_b} \tag{10}$$

where μ represents the brightness; δ indicates the contrast of the image; C_a and C_b are two constants.

The experiment will be divided into two parts. The first is used to verify the efficiency advantage of the AHS-Otsu compared with the original Otsu in multilevel threshold segmentation. The second is used to prove the better performance of AHS-Otsu in image segmentation compared with other algorithms.

All the experiment codes are executed on MATLAB 2022a, and the computer configuration is: Windows 10 system, Intel (R) Core (TM) i7-10510U CPU @ 1.80GHz processor, 8.00G RAM and 1T storage.

4.1. Verification of Image Segmentation Efficiency

In this subsection, the efficiency of AHS-Otsu is compared with the original Otsu method. For AHS-Otsu algorithm, the number of iterations is set 500, and other suitable parameters are set as: *HMS*=20, *HMCR*=0.99, while the value of PAR is obtained according to Eq. (6) and is no longer pre-setting manually. All images are divided into “m=2, 3, 4, 5” regions by the two segmentation schemes respectively.

The processing time (unit: second) and the PSNR values of image segmentation metric are recorded in Table 1. From Table 1, the PSNR values between AHS-Otsu and Otsu are the same, which indicate they got the same segmentation performance. However, for the basic Otsu method, the segmentation time increases exponentially with the threshold number, thus gradually losing its effectiveness. While for the image segmentation based on the AHS-Otsu, although the operation time at “m=2” is not as good as Otsu, the time consumption is always short as the segmentation threshold number increases.

From this experiment, the image multi-threshold segmentation performed by AHS-Otsu can obtain the actual threshold results in a short time, which indicates its high efficiency and can be regarded as a successful segmentation method.

4.2. Comparison of Image Segmentation Capabilities

For this subsection, six other well-known HS algorithms will be used to compare the accuracy in image segmentation with the proposed AHS, which include HS, IGHS, GHS, HHS [18], PAHS-3 [19] and IGHS [20]. All the approaches take the maximum between-class variance as the objective function, and perform image multi-threshold segmentation with “m=3, 4, 5”. Each method executes 500 optimization iterations and run 30 trials independently.

Figure 4 present the convergence curves from the different algorithms on the representative multi-threshold image segmentation, which include “m=2” for “I1”, “m=3” for “I2”, “m=4” for “I3”, “m=5” for “I4”, “m=3” for “I5”, “m=4” for “I6”. The values show in graphs are the average optimal results from independent experiment of each method. As can be seen from the graphs, the optimization curves of AHS are always at the highest values required. Furthermore, the AHS reaches the optimal values faster than other algorithms, which indicates its higher optimization speed and accuracy in image segmentation.

Table 1. *Comparison of image segmentation results using Otsu and AHS-Otsu.*

Image		**m= 2**		**m= 3**		**m= 4**		**m=5**	
		Otsu	**AHS-Otsu**	**Otsu**	**AHS-Otsu**	**Otsu**	**AHS-Otsu**	**Otsu**	**AHS-Otsu**
I1	Time (s)	0.016	0.098	0.236	0.102	6.306	0.111	672.406	0.114
	PSNR	8.468	8.468	12.660	12.660	15.313	15.313	32.519	32.519
I2	Time (s)	0.015	0.087	0.245	0.097	6.210	0.105	694.827	0.108
	PSNR	8.315	8.315	16.003	16.003	18.468	18.468	34.814	34.814
I3	Time (s)	0.014	0.095	0.239	0.114	7.188	0.117	618.147	0.117
	PSNR	8.167	8.167	14.050	14.050	15.882	15.882	32.823	32.823
I4	Time (s)	0.017	0.095	0.222	0.096	5.347	0.094	673.506	0.113
	PSNR	9.836	9.836	11.531	11.531	17.928	17.928	34.034	34.034
I5	Time (s)	0.017	0.091	0.221	0.093	5.291	0.109	642.521	0.111
	PSNR	6.812	6.812	16.596	16.596	20.495	20.495	35.428	35.428
I6	Time (s)	0.014	0.088	0.238	0.093	5.435	0.096	696.203	0.106

Image	m= 2		m= 3		m= 4		m=5	
	Otsu	AHS-Otsu	Otsu	AHS-Otsu	Otsu	AHS-Otsu	Otsu	AHS-Otsu
PSNR	9.937	9.937	12.626	12.626	16.441	16.441	36.069	36.069

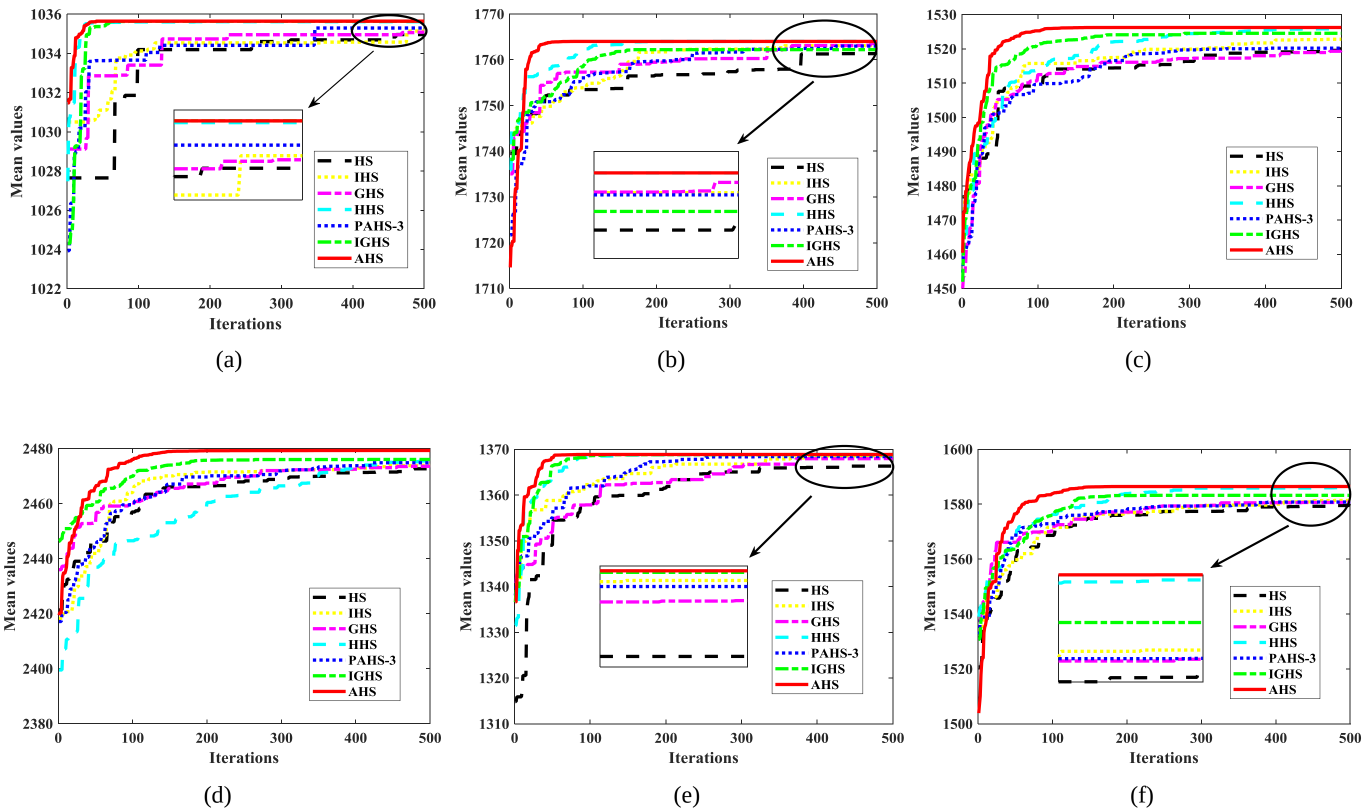

Figure 4. Optimization convergence curves for image segmentation (a: "m=2" for "I1", b: "m=3" for "I2", c: "m=4" for "I3", d: "m=5" for "I4", e: "m=3" for "I5", f: "m=4" for "I6").

Table 2. PSNR values of different HS algorithms in image segmentation.

Image	Region	HS-Otsu	IHS-Otsu	GHS-Otsu	HHS-Otsu	PAHS-3-Otsu	IGHS-Otsu	AHS-Otsu
I1	3	23.9339	23.9098	23.8775	23.9417	23.883	23.9421	23.9421
	4	26.2078	26.2287	26.276	26.3004	26.2566	26.3058	26.3081
	5	27.6763	27.6078	27.5073	27.719	27.3715	27.7361	27.8095
I2	3	22.0047	22.017	21.843	21.9811	22.0047	21.9811	22.0345
	4	26.1539	26.228	26.2588	26.2628	26.1845	26.1678	26.2666
	5	28.0522	27.9551	27.7729	28.5355	28.1322	28.4981	28.5377
I3	3	23.4997	23.4036	23.4738	23.5012	23.4998	23.5012	23.5012
	4	26.0903	26.0988	26.1151	26.1217	25.8098	26.1111	26.1227
	5	27.4931	27.6748	27.8609	28.0167	27.6853	27.9888	28.0188
I4	3	22.9618	22.97	22.909	22.9805	22.9444	22.9673	22.9805
	4	24.8484	24.5768	24.9138	24.5357	24.9103	24.8004	24.9316

Image	Region	HS-Otsu	IHS-Otsu	GHS-Otsu	HHS-Otsu	PAHS-3-Otsu	IGHS-Otsu	AHS-Otsu
	5	26.5602	26.4402	26.6048	26.6168	26.176	26.6585	26.6747
I5	3	23.2634	23.2668	23.2693	23.2796	23.2798	23.2798	23.2798
	4	25.6289	25.6071	25.5851	25.666	25.6245	25.5415	25.6624
	5	27.6564	27.5769	27.4263	27.6878	27.437	27.3267	27.7061
I6	3	22.6691	22.6691	22.6749	22.6781	22.6727	22.6781	22.6781
	4	24.6835	24.7637	24.7485	24.8447	24.819	24.5947	24.7562
	5	26.7793	26.7025	26.1221	26.8527	26.5785	26.8379	26.8666

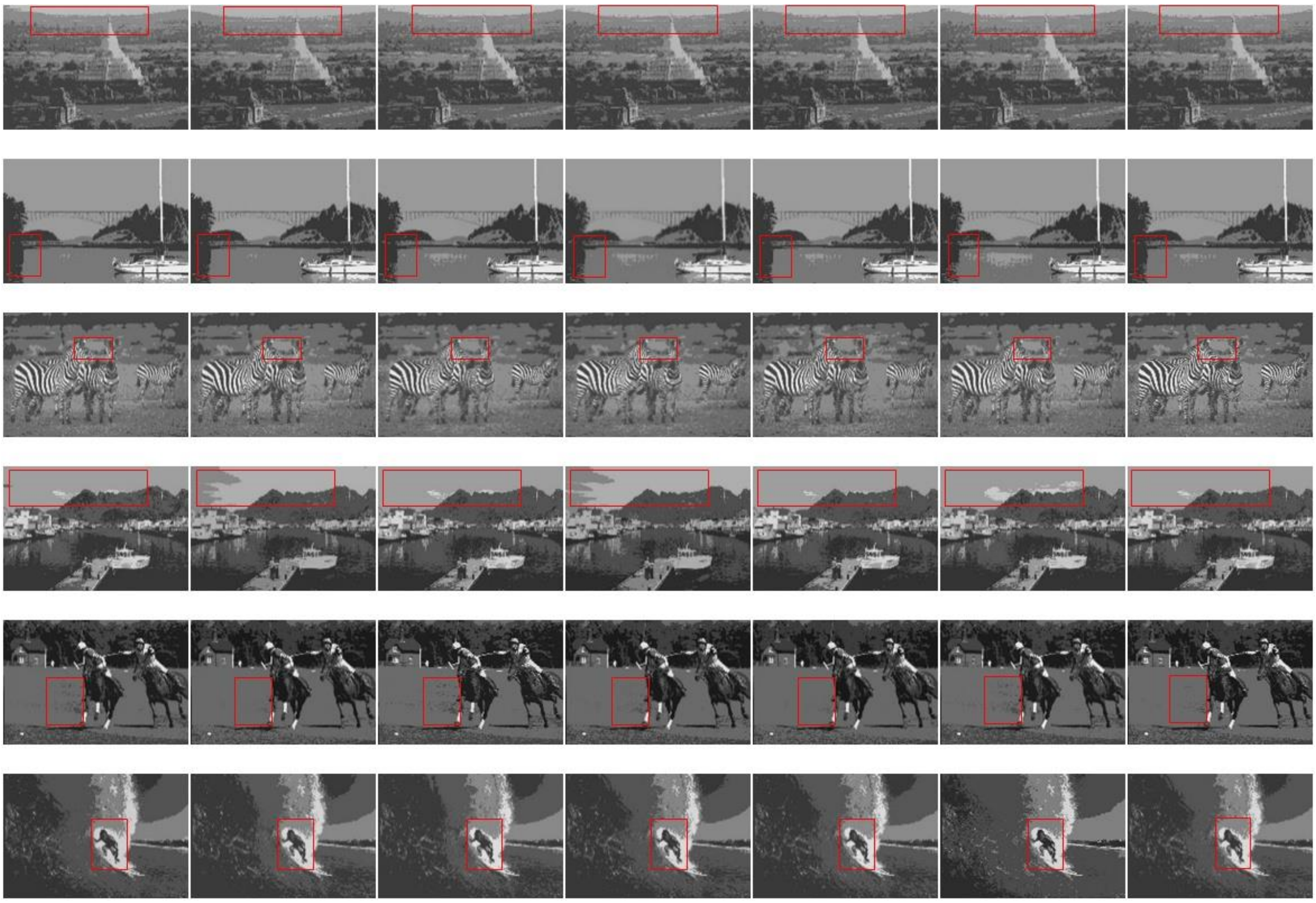

Figure 5*. Segmentation performance with "m=4" for each method (from left to right: HS-Otsu, IHS-Otsu, GHS-Otsu, PAHS-3-Otsu, IGHS-Otsu, AHS-Otsu).*

Table 3*. SSIM values of different HS algorithms in image segmentation.*

Image	Region	HS-Otsu	IHS-Otsu	GHS-Otsu	HHS-Otsu	PAHS-3-Otsu	IGHS-Otsu	AHS-Otsu
I1	3	0.6619	0.6584	0.6721	0.6565	0.6368	0.6537	0.6537
	4	0.721	0.7405	0.7281	0.7356	0.7335	0.7317	0.7337
	5	0.7698	0.7862	0.7461	0.7711	0.7754	0.7755	0.7872
I2	3	0.5884	0.5861	0.5904	0.5878	0.5884	0.5878	0.5898
	4	0.8307	0.8336	0.8268	0.8263	0.8249	0.8195	0.8289

Image	Region	HS-Otsu	IHS-Otsu	GHS-Otsu	HHS-Otsu	PAHS-3-Otsu	IGHS-Otsu	AHS-Otsu
	5	0.8526	0.8571	0.8611	0.8764	0.8583	0.8749	0.8755
I3	3	0.7125	0.704	0.7116	0.7129	0.7124	0.7129	0.7129
	4	0.7803	0.78	0.7837	0.7796	0.7806	0.779	0.7815
	5	0.8174	0.8103	0.8375	0.8363	0.8265	0.8385	0.8358
I4	3	0.7457	0.7426	0.736	0.743	0.7431	0.7436	0.743
	4	0.7649	0.7649	0.7617	0.7571	0.7647	0.7594	0.7652
	5	0.7911	0.7833	0.7971	0.8061	0.7973	0.7922	0.7897
I5	3	0.6367	0.6393	0.6398	0.6384	0.6385	0.6385	0.6385
	4	0.6998	0.7078	0.7003	0.7053	0.7088	0.698	0.7023
	5	0.7682	0.7601	0.7654	0.7713	0.76	0.7639	0.7707
I6	3	0.7263	0.7263	0.7264	0.7264	0.726	0.7264	0.7264
	4	0.7517	0.765	0.7666	0.759	0.7604	0.7251	0.7546
	5	0.7913	0.7924	0.7734	0.7946	0.7916	0.7904	0.7947

The PSNR and SSIM values of image multi-threshold segmentation (m=3, 4, 5) obtained by different algorithms are recorded in Table 2 and Table 3 respectively, the best results are marked in bold. From the data, it can be seen that the AHS-Otus acquires the best outcomes in most cases. For IGHS-Otsu, although it can be comparable to AHS-Otsu in "m=3" threshold, its segmentation effect becomes worse as the number of thresholds increase. While for the remaining methods, they failed to get the best results in image multi-threshold segmentation. In addition, the effect of image segmentation reflected by the two metrics is basically the same.

In order to observe the performance more intuitively, Figure 5 present the segmentation results of each algorithm on the test images with the condition of "m=4". It can be seen that compared with other approaches, the AHS-Otsu owns stronger segmentation ability for image details, which are mainly displayed in the mountain in I1, the trees in I2, the grass in I3, the cloud in I4, the background in I5, and the person in I6. All the above descriptions are marked in the images.

Based on the experimental results, compared with other typical HS approaches, the AHS used in image segmentation, namely AHS-Otus, not only has the ability of fast convergence, but also can improve the convergence accuracy, which will be applied to the image multi-threshold segmentation problem effectively.

5. Conclusions

To address the issues of time consumption and low accuracy of traditional image multi-threshold segmentation methods, a new multilevel thresholding strategy named AHD-Otus which based on an ameliorated harmony search (AHS) is put forward in this article. By modifying the operation of the new harmony generation, the proposed AHS can increase the diversity of numerical search, thus improving the optimization rate and accuracy. Take the maximum between-class variance as the objective function, the AHS-Otus method can be applied to image multi-threshold segmentation.

To verify the effectiveness of the AHS-Otsu, six test images are selected for the comparative experiments. Firstly, compare the segmentation efficiency between AHS-Otsu and Otsu, which indicates the AHS-Otsu takes less time than Otsu, but can obtain the similar segment performance. Secondly, compare the AHS with several other well-known HS algorithms used in image segmentation, the AHS-Otus put forward outperforms other methods in resulting higher quality of image multi-threshold segmentation. Thus, the AHS-Otsu can be recognized as a potential new image multilevel segmentation algorithm.

Abbreviations

HMS	Harmony Memory Size
HMCR	Harmony Memory Consideration Rate
PAR	Pitch Adjustment Rate
bw	Distance Bandwidth
NI	Number of Improvisations

Author Contributions

Xiuteng Shu: Investigation, Formal Analysis, Data curation

Xiangmeng Tang: Conceptualization, Resources, Methodology, Writing – original draft

Funding

This work is supported by Shandong Provincial Natural Science Foundation (ZR2022QF149).

Conflicts of Interest

The authors declare no conflicts of interest.

References

[1] Sakshi, Kukreja V. Image Segmentation Techniques: Statistical, Comprehensive, Semi-Automated Analysis and an Application Perspective Analysis of Mathematical Expressions [J]. Archives of Computational Methods in Engineering, 2023, 30(1): 457-495. https://doi.org/10.1007/s11831-022-09805-9

[2] Jiang Z, Zou F, Chen D B, et al. An ensemble multi-swarm teaching-learning-based optimization algorithm for function optimization and image segmentation [J]. Appl. Soft Comput. 2022, 130: 109653. https://doi.org/10.1016/j.asoc.2022.109653

[3] Wu, Qiang. Microscope Image Processing || Image Segmentation [J]. 2008: 159-194. https://doi.org/10.1016/B978-0-12-372578-3.00009-X

[4] Abualigah L, Almotairi K H, Elaziz M A. Multilevel thresholding image segmentation using meta-heuristic optimization algorithms: comparative analysis, open challenges and new trends [J]. Applied Intelligence, 2022: 1-51. https://doi.org/10.1007/s10489-022-04064-4

[5] Gao H, Shi Y, Pun C M, et al. An Improved Artificial Bee Colony Algorithm With its Application [J]. IEEE transactions on industrial informatics, 2019(4). https://doi.org/10.1109/tii.2018.2857 -198

[6] Otsu N. A Threshold Selection Method from Gray-Level Histograms [J]. IEEE Transactions on Systems, Man, and Cybernetics, 1979, 9(1): 62-66. https://doi.org/10.1109/TSMC.1979.431 0076

[7] Qin J, Shen X, Mei F, et al. An Otsu multi-thresholds segmentation algorithm based on improved ACO [J]. The Journal of Supercomputing, 2019, 75(2): 955-967. https://doi.org/10.1007/s-11227-018-2622-0

[8] Al-Rahlawee A T H, Rahebi J. Multilevel thresholding of images with improved Otsu thresholding by black widow optimization algorithm [J]. Multimedia Tools and Applications, 2021, 80(2–3). https://doi.org/10.1007/s11042-021-10860-w

[9] Banerjee S, Mitra S, Uma Shankar B. Single seed delineation of brain tumor using multi-thresholding [J]. Information Sciences, 2016: 88-103. https://doi.org/10.1016/j.ins.2015.10.018

[10] Huang C, Li X, Wen Y. AN OTSU image segmentation based on fruitfly optimization algorithm [J]. AEJ - Alexandria Engineering Journal, 2020. https://doi.org/10.1016/j.aej.2020.06.054

[11] Pare S, Kumar A, Singh G K, et al. Image Segmentation Using Multilevel Thresholding: A Research Review [J]. Iranian Journal of Science and Technology, Transactions of Electrical Engineering, 2020, 44(1): 1-29. https://doi.org/10.1007/s40998-019 -00251-1

[12] Shu-Liang W, He-Ji Z. Multilevel thresholding gray-scale image segmentation based on improved particle swarm optimization [J]. Journal of Computer Applications, 2012. https://doi.org/10.1007/978-3-642-25538-0_26

[13] Sathya P D, Kayalvizhi R. Modified bacterial foraging algorithm based multilevel thresholding for image segmentation [J]. Engineering Applications of Artificial Intelligence, 2011, 24(4): 595-615. https://doi.org/10.1016/j.engappai.2010.12.001

[14] Geem Z W, Kim J H, Loganathan G V. A New Heuristic Optimization Algorithm: Harmony Search [J]. Simulation, 2001, 2(2): 60-68. https://doi.org/10.1177/003754970107600201

[15] Zhu Q, Tang X, Li Y, et al. An improved differential-based harmony search algorithm with linear dynamic domain [J]. Knowledge-Based Systems, 2020, 187(Jan.): 104809.1 -104809.14. https://doi.org/10.1016/j.knosys.2019.06.017

[16] Kang J, Kwon S, Ryu D, et al. HASPO: Harmony Search-Based Parameter Optimization for Just-in-Time Software Defect Prediction in Maritime Software [J]. Applied Sciences, 2021, 11(5): 2002. https://doi.org/10.3390/app11052002

[17] Dubey M, Kumar V, Kaur M, et al. A Systematic Review on Harmony Search Algorithm: Theory, Literature, and Applications [J]. Mathematical Problems in Engineering, 2021. https://doi.org/10.1155/2021/5594267

[18] Cheng M Y, Prayogo D, Wu Y W, et al. A Hybrid Harmony Search algorithm for discrete sizing optimization of truss structure [J]. Automation in Construction, 2016, 69(SEP.): 21 -33. https://doi.org/10.1016/j.autcon.2016.05.023

[19] Kumar V, Chhabra J K, Kumar D. Parameter adaptive harmony search algorithm for unimodal and multimodal optimization problems [J]. Journal of Computational Science, 2014, 5(2): 144-155. https://doi.org/10.1016/j.jocs.2013.12.001

[20] Xiang W L, An M Q, Li Y Z, et al. An improved global-best harmony search algorithm for faster optimization [J]. Expert Systems with Applications, 2014, 41(13): 5788-5803. https://doi.org/10.1016/j.eswa.2014.03.016

Biography

Xiuteng Shu is pursuing his master's degree at Shandong Jiaotong University. He obtained his bachelor degree of Engineering from Shandong Jiaotong University in 2024. During his undergraduate studies, he achieved excellent results in course and participated in multiple robot related competitions. With his outstanding leadership and teamwork abilities, he led the team to win multiple awards.

Xiangmeng Tang is a lecturer and master tutor at Shandong Jiaotong University. He received his Ph.D. degree from Harbin Engineering University in 2022 and joined Shandong Jiaotong University. He has been published several SIC papers, also served as a reviewer of several SCI journals. His current research fields are optimization algorithms, image processing and data mining.

Research Field

Xiuteng Shu: Image Processing
Xiangmeng Tang: Optimization algorithms, Image processing, Data mining