SEGMENTATION OF LUNG CANCER CT IMAGES BY MULTI-LEVEL OTSU THRESHOLDING USING SINE COSINE OPTIMIZATION ALGORITHM

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Article History: Received: 21.03.2023 **Revised:** 06.04.2023 **Accepted:** 22.04.2023 **Published:** 21.05.2023

Abstract

Many image processing methods start with an important first step called picture thresholding, which aids in accurate image segmentation and effective prediction. The Sine Cosine Technique is a meta heuristic optimization algorithm that beats several traditional algorithms due to its special premise. Lung cancer CT images were employed in this study because it is one of the most lethal diseases and accounts for a substantial number of fatalities globally. This work demonstrates the application of the Otsu multi thresholding objective function and Sine Cosine nature inspired optimization algorithms on computed tomography (CT) pictures of lung cancer. The suggested method leverages the SCA algorithm's object function, which aids in the selection of elite candidates, to apply the Otsu multi thresholding technique to a CT image.

Keywords: Image Segmentation, Otsu, Multi-Level Thresholding, SCA

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DOI: 10.31838/ecb/2023.12.s2.362

1. Introduction

Nature-inspired algorithms are currently very well-liked because of their capacity to provide precise results in challenging optimization challenges. Many of the algorithms that take their cues from nature are actually meta-heuristic optimization methods. The population of candidate solutions could grow as a result of these methods. Given that it is one of the leading causes of death worldwide, cancer is among the most dangerous diseases affecting both men and women. Even though it is a time-consuming process that frequently leads to pathologists disagreeing, early diagnosis increases the likelihood of effective therapy and survival. On the other hand, early detection and prevention will greatly reduce the risk of death. Lung cancer can be diagnosed using computed tomography (CT) scans [8]. A crucial stage in image processing is image segmentation, which involves dividing an image into non-overlapping regions or classes based on similarities in colour, texture, brightness, and contrast using predetermined processes referred to as objective functions [4]. Camera segmentation is useful for video surveillance, traffic control systems, medical pictures, item detection, satellite images, and object recognition. However, the main goal of segmentation is to convert each image into one that can be understood more precisely [9], which calls for identifying homogeneous groupings. One of the most well-liked and widely applied image processing techniques is thresholding. These techniques offer a threshold value that can be used to distinguish between foreground and background in a picture. The region is regarded as black and the rest values as white when the pixel values are below the threshold value. The following is one of the most widely used picture segmentation strategies out of the many that may be used. Threshold Based, Edge Based, Clustering Bases, Region Based, Artificial Neural Network, Partial Deferential Equation, Watershed Based, are only a few examples. [4]. Three categories can be used to group thresholding techniques. Bit level thresholding is the first, followed by multilayer thresholding and local thresholding. [4]. One of the most popular thresholding techniques is otsu. The estimate of the mean quantities of two groups split by this threshold is known as the Otsu threshold.The algorithm, in general, returns a threshold value that converts a grayscale image to a binary image. An image can be defined as I(x, y) with a gray level range from 0 to L−1, where L is the number of distinct gray levels. Let the number of pixels with the gray-level i be n_i, and n be the total number of pixels in a given image with the size of M × N. The probability of occurrence of the gray level i is defined as follows.

pi = n_i/n (1)

[XiangyangXu, Ta Yang Goh, Xiao-cui Yua, XiaoliZhang] If a threshold t splits an image into two groups, D0 and D1, D0 contains pixels with levels [0, t], and D1 includes pixels with levels [t + 1, L 1]. P_0(t) and P_1(t) are the cumulative probabilities, while u_0(t) and u_1(t) are the mean levels of the D0 and D1classes, respectively.

$$P_0(T) = \sum_{i=1}^{T} p_i \quad (2)$$
$$P_1(T) = \sum_{i=T+1}^{L} p_i = 1 - P_0(T) \quad (3)$$
$$\mu_0(T) = \sum_{i=1}^{T} i\,\frac{p_i}{P_0(T)} = \frac{1}{P_0(T)}\sum_{i=1}^{T} i\,p_i \quad (4)$$
$$\mu_1(T) = \sum_{i=T+1}^{L} i\,\frac{p_i}{P_1(T)} = \frac{1}{P_1(T)}\sum_{i=T+1}^{L} i\,p_i \quad (5)$$
$$\sigma_0^2(T) = \sum_{i=1}^{T}(\,i - \mu_0(T))^2\,\frac{p_i}{P_0(T)} \quad (6)$$
$$\sigma_1^2(T) = \sum_{i=T+1}^{L}(\,i - \mu_1(T))^2\,\frac{p_i}{P_1(T)} \quad (7)$$

Let , $\sigma_b^2(T)$, and $\sigma_w^2(T)$ represent the mean level of the image, the between-class variance, and the within-class variance, respectively [25, 9, 27, 8]:

$$\mu = \sum_{i=1}^{L} i\,p_i = P_0(T)\mu_0(T) + P_1(T)\mu_1(T) \quad (8)$$
$$\sigma_b^2(T) = P_0(T)(\mu_0(T) - \mu)^2 + P_1(T)(\mu_1(T)\mu)^2 \quad (9)$$
$$\sigma_w^2(T) = P_0(T)\sigma_0^2(T) + P_1(T)\sigma_1^2(T) \quad (10)$$

The threshold decided by maximizing the between-class variance proposed in Otsu is:

$$T^* = 1 \le T < L \text{ arg } \max\{\sigma_b^2(T)\} \quad (11)$$

This value is equal to the threshold decided by minimizing the within-class variances criterion:

$$T^* = l \le T < L \text{ arg } \mathrm{m}in\{\sigma_w^2(T)\} \quad (12)$$

Moreover, the above threshold is same as the threshold calculated by maximizing the ratio of between class variance to within class variances [25, 9, 27, 8]. Optimization means process of finding elite solution to the given parameter values from all possible values to minimize or maximize the output. Really it is a population based, which performs based on set of random values. There are two optimization phases in SCA algorithm exploration and exploitation. There are continues changes in the random solutions of exploitation phase, and in the exploration phase random variations are drastically less. The following equations are proposed for updating phases are

$$X_i^{T+1} = X_i^T + r_1 \times \sin(r_2) \times |r_3 P_i^T - X_i^T| \quad (13)$$
$$X_i^{T+1} = X_i^T + r_1 \times cos(r_2) \times |r_3 P_i^T - X_{i_i}^T| \quad (14)$$

Where X_i^{ζ} is the position of the current solution in i^{th} dimension at t^{th} iteration, r_1, r_2, r_3 are random numbers, P_i is position of the destination point in i^{th} dimension, and | | indicates the absolute value. The above two equations are combined to be used as follows:

$$X_i^{T+1} = \begin{cases} X_i^T + r_1 \times \sin(r_2) \times |r_3 P_i^T - X_i^T|, & r_4 < 0.5 \\ X_i^T + r_1 \times cos(r_2) \times |r_3 P_i^T - X_{i_L}^T|, & r_4 \geq 0.5 \end{cases} \quad (15)$$

Where r_4 is random number in range [0, 1] and r_1 is following equation.

$$r_1 = a - t\frac{a}{T} \quad (16)$$

where t represents the current iteration, T represents the cumulative number of iterations, and a represents the constant. r_1, r_2, r_3, and r_4 are the four most important parameters in SCA. Here, r1 denotes the next location area, which may be within or outside the space between the solution and the destination. The r_2 parameter specifies how far the movement can be in the direction of the destination or outwards. The r_3 parameter assigns random weights to the destination in order to stochastically emphasise (r_3> 1) or deemphasize (r_3<1) the desalination effect in determining the radius. Finally, the r_4 parameter alternates between sine and cosine elements in equation:14[13, 17, 18].

Literature Survey

The Otsu Multi threshold, Sine Cosine Algorithm with Lung Cancer CT Images is described in detail in this section, along with a related work on these algorithms.

Otsu Multi Threshold

For algorithms for picture recognition, object representation, and visualisation [25], image thresholding is frequently the first step. In their study, they outlined the properties of the Otsu system and demonstrated that it is comparable to the product of the mean levels of two groups divided by a threshold. The Otsu system is the primary focus, claim the authors. According to the image thresholding methodology, which is based on the Monte Carlo statistical procedure, the impacts of picture segmentation depend on the size, noise computation, and object context intensity difference but are unaffected by the position of the object on the suggested method.

$Y_b(t) = \omega P_0(t)(u_0(t))^2 + P_1(t)(u_1(t))^2$ (17)

TH =arg $\max_{1<t<L} Y_b(t)$ (18)

= arg max $_{1<t<L}$ $(\omega P_0(t)(u_0(t))^2 + P_1(t)(u_1(t))^2)$

In Equation (16), the parameter ω is a weight of the object variance, and the value of ω is ranged from 0 to 1. As ωP0(t)(u0(t))2 + P1(t)(u1(t))2 the threshold value of the proposed method is equal to or smaller than the Otsu's threshold. As ω is ranged from 0 to 1, we select ω = 0.1[27]. By taking into account the high resolution 3D Otsu, a novel multi thresholding algorithm 3D Otsu and multi-scale image representation for medical image segmentation has been proposed [8]. Huang proposed a procedure for detecting cracks in concrete structure images by identifying three steps, one of which is transforming the given picture to a grey image for crack detection. The second step is to transform an image to binary using threshold values, and the third step is to use the Otsu process to identify large cracks. [23].

Sine Cosine Algorithm

For algorithms for picture recognition, object representation, and visualisation [25], image thresholding is frequently the first step. In their study, they outlined the properties of the Otsu system and demonstrated that it is comparable to the product of the mean levels of two groups divided by a threshold. The Otsu system is the primary focus, claim the authors. According to the image thresholding methodology, which is based on the Monte Carlo statistical procedure, the impacts of picture segmentation depend on the size, noise computation, and object context intensity difference but are unaffected by the position of the object on the suggested method. The sine cosine algorithm's weak exploitation, skipping of real solutions, and insufficient compromise between discovery and exploitation are addressed by the suggested enhanced variation of SCA, known as HSCA. Four engineering optimization issues, as well as the common and complicated benchmark sets IEEE CEC 2014 and CEC 2017, were used to test the suggested methodology[10]. A SCA skips real solutions and becomes trapped at imperfect answers. These problems cause premature convergence, which is detrimental for assessing global optimum. elicit support for the sine cosine and grey wolf optimizer (SCGWO) algorithms [14]. We established balanced and explorative search control in SCA for potential solutions by putting forth a novel technique dubbed the memory driven sine cosine algorithm (MG-SCA). The number of guides in MGSCA reduces as the number of iterations increases in order to maintain a suitable balance between discovery and exploitation. The effectiveness of the suggested MG-SCA is assessed on a number of traditional test issues, IEEE CEC 2014 challenges, and four well-known engineering benchmark problems [12]. The MMSCA method, which has been developed, runs numerous populations concurrently, each population using a distinct optimization technique and exchanging information via global communication [26]. An alternate hybrid strategy for automatic clustering has been presented by combining the sine cosine algorithm and meta-heuristic atom search optimization (ASO) (SCA). Calculating the number of clusters and their centre automatically is the main objective of the suggested approach (ASOSCA). In order to accomplish this, ASOSCA uses SCA operators as a local search strategy to enhance ASO convergence and find the optimal solution [5]. A novel thresholding technique for medical picture segmentation combining 3D Otsu and multi-scale image representation was presented [8], taking into account the high temporal complexity of the 3D Otsu approach.

2. Methodology

Compared to other techniques, the Otsu thresholding technique takes less calculation time to segment the given image. The Otsu thresholding method uses random variables and simple sine and cosine mathematical equations in its algorithm to find the appropriate threshold value. The proposed methodology is composed of five steps. Giving CT scans to the algorithm as input, creating a histogram, initialising SCA parameters, initialising the population of search agents, determining the elite solution by putting the algorithm into practise, and repeating the process till the requirement is satisfied. The steps done in the suggested strategy are shown in Figure 1. Computed tomography images were acquired in the first stage, and histograms were generated for each picture in the second. The sine cosine algorithm's parameter values are initialised at the following step, which is followed by the population of search agents. The sine and cosine trigonometric functions' mathematical features served as the basis for the nature-inspired population-based algorithm known as SCA. SCA uses two opposing strategies while conducting a search. Exploration is the process of identifying new, prospective search space regions, whereas exploitation is local search, which is done within designated search space regions. Each potential solution is altered using search eq.15 after SCA randomly starts the search process. Random generation has produced the population and workable solutions. Then, in the subsequent steps, the population of search agents is initialised by randomly generating lower and upper boundaries The next step is to update the search agent's position. The next step is to update the destination position of the elite solution that has already been developed thus far and analyse the search agent using the Otsu objective feature, provided that the termination condition is satisfied. Image segmentation will be successfully completed if all of the processes have been successfully completed.

Procedure for the SCA Algorithm:

Initialize a set of potential solutions.

Step 2: Determine the suitability of each potential option.

Initialize the parameters r1 and tmax in step 3.

Step 4: Update each candidate solution using SCA search equation 15.

Update control parameter r1 in step 5.

Steps 4 and 5 should be repeated until the termination condition is met before updating the destination point.

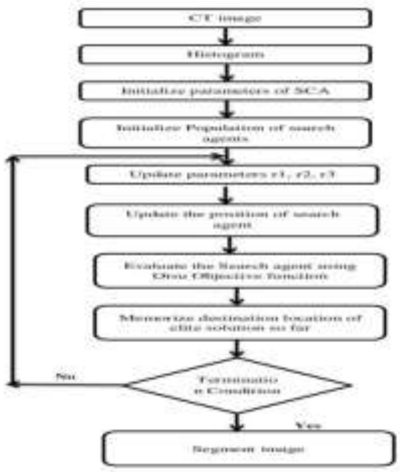

Figure1: Proposed methodology Flow chart

3. Results

In this section, the proposed methodology's experimental findings are extended to nine large scale CT lung cancer image dataset collected from the Cancer Image Database (TCIA).

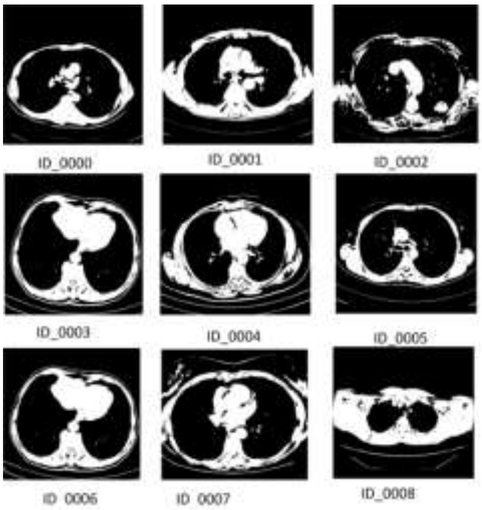

Figure 2: Nine Lung Cancer CT images

Figure 2 shows input images. The measurement results of experiments are given in terms of various performance measurements such as PSNR, SSIM, and computational time. In this experiment, all of the necessary parameters are initially set as

Otsu Thresholding

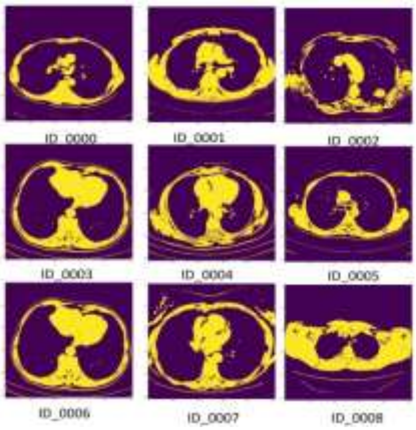

Figure 3: Output images of Otsu image Segmentation

and the population size is equal to the number of threshold values used to segment the images, initialized random variable $r_{1,}$ $r_{2,}$ and r_3 and initialized r_4 values between 0, 1.Otsu's thresholding method involves iterating through all the possible threshold values and calculating a measure of spread for the pixel levels each side of the threshold, i.e. the pixels that either fall in foreground or background. This approach has been implemented to input images in fugure2 and we got the same output as in fugure3. The findings are seen in the table below, and it has been discovered that the SSIM, PSNR, and CPU time are all high.

Image	SSIM	PSNR	CPU time
ID_0000	0.97573	35.243648	0.84373
ID_0001	0.9758136	34.616582	0.78122
ID_0002	0.967752	33.08618	0.765621
ID_0003	0.9738142	33.586666	0.78122
ID_0004	0.9662845	32.658015	0.8122
ID_0005	0.9732484	34.89693	0.8123

ID_0006	0.9738143	33.586667	0.78121
ID_0007	0.9641422	32.81224	1.621
ID_0008	0.9817074	35.566403	0.8122

Table1: Results of Otsu Object function

Multi-Level Thresholding
Whenever this approach is initialized threshold values to five classes and applied them to the input images, it was noticed that there is difference in the output images and that the effects are very good when comparing to Otsu thresholding. Figure 4 is an output image of multi-level thresholding.

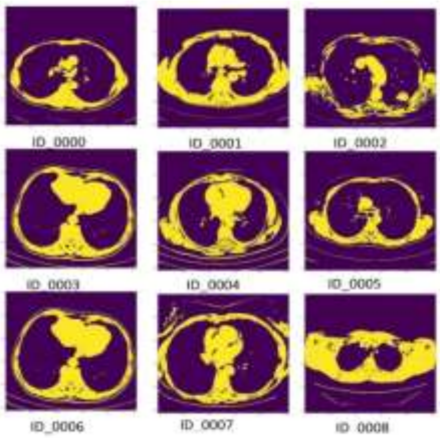

Figure 4: Multi-Level Thresholding image Segmentation

Table 2 discussed the results of an algorithm, as compared to the Otsu algorithm, the SSIM and PSNR values increase, and the computation time is reduced.

Image	SSIM	PSNR	CPU time
ID_0000	0.759163	39.336811	5.390623
ID_0001	0.6540814	37.843414	5.515621
ID_0002	0.6785035	37.699912	6.453122
ID_0003	0.6042941	37.249243	5.984374
ID_0004	0.5832143	36.713615	6.046877
ID_0005	0.7287231	38.892462	5.9373
ID_0006	0.6042945	37.249245	6.371
ID_0007	0.5962548	37.0101	5.90626
ID_0008	0.6637867	38.054753	6.015627

Table2: Results of Multi level Thresholding Otsu Object function

SCA Multi Thresholding algorithm
Figure 1 represents the original to nine large scale CT lung cancer image dataset (TCIA).The proposed procedure is tested for different threshold values such as 3, 5, and 7. Table 3 shows the PSNR, SSIM, and computational time values for the proposed system with thresholds of 3, 5, and 7. Figure 5 displays the images produced after implementing the procedure of threshold values. Table 3 displays the average values of all performance indicators.

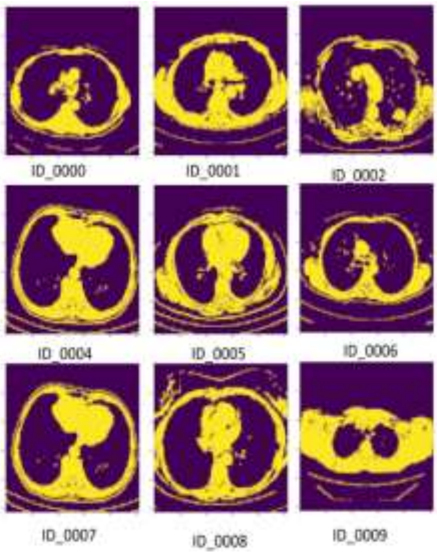

Figure 5: Proposed Sine Cosine Multi-Level Thresholding image segmentation

The proposed method outperforms the Otsu method by a substantial margin and the multi outs method .

Iterations	Image	SSIM	PSNR	CPU time
3	**ID_0000**	0.674983	39.343	0.296873
	ID_0001	0.583094	37.90721	0.28122
	ID_0002	0.610788	37.90305	0.46873
	ID_0003	0.54213	37.40897	0.640622
	ID_0004	0.528831	36.86225	0.609374
	ID_0005	0.650702	38.96741	0.28126
	ID_0006	0.54211	37.40897	0.28127
	ID_0007	0.541153	37.16822	0.28121
	ID_0008	0.587742	38.01255	0.28123
	Average	**0.584616**	**37.88708**	**0.380208**
Iterations	**Image**	**SSIM**	**PSNR**	**CPU time**
5	**ID_0000**	0.694677	39.40623	0.421873
	ID_0001	0.594511	37.96412	0.6874
	ID_0002	0.646895	37.9054	0.703123
	ID_0003	0.562313	37.42186	0.359371
	ID_0004	0.542355	36.89233	0.328122
	ID_0005	0.674467	38.98671	0.3124
	ID_0006	0.575833	37.43753	0.328126
	ID_0007	0.56232	37.25421	0.40627
	ID_0008	0.597147	38.16592	0.6878
	Average	**0.595618**	**36.93718**	**0.460486**
Iterations	**Image**	**SSIM**	**PSNR**	**CPU time**
7	**ID_0000**	0.707323	39.51562	0.374
	ID_0001	0.595952	37.97923	0.390623
	ID_0002	0.610787	37.93414	0.390622
	ID_0003	0.54214	37.54271	0.390624
	ID_0004	0.586926	36.92186	0.35936
	ID_0005	0.650704	38.98824	0.40626

	ID_0006	0.602359	37.45315	0.4377
	ID_0007	0.628681	37.29596	0.359373
	ID_0008	0.607222	38.21063	0.359378
	Average	**0.614675**	**37.98238**	**0.385417**

Table 3: Average values of PSNR, SSIM and Computational time for nine images with five different thresholds and 3, 5, 7 iterations.

merely marginally. The most important factor for evaluating the effectiveness of image processing is PSNR. The observed values for nine photos with identical threshold values are displayed in Table 4. The total computational time is displayed in Table 6. It is found that, in comparison to the other two approaches, the suggested solution requires the least amount of time. The suggested approach performs better than equivalent techniques., as seen in Tables 4, 3, and 6.

Image	Otsu	Multi_Otsu	SCA_Multi_Otsu
ID_0000	35.243649	39.336813	37.29023074
ID_0001	34.616581	37.843416	36.22999842
ID_0002	33.08617	37.699914	35.39304161
ID_0003	33.586669	37.249247	35.41795793
ID_0004	32.658017	36.713616	34.68581635
ID_0005	34.89691	38.892466	36.89468761
ID_0006	33.586669	37.249247	35.41795793
ID_0007	32.81226	37.0102	34.91123031
ID_0008	35.566405	38.054752	36.81057842

Table 4: Average PSNR Values.

Table 5 shows the average SSIM values of nine images generated using three different approaches. It is observed that the proposed approach outperforms the Multi otsu method by a small margin.

Image	Otsu	Multi_Otsu	SCA_Multi_Otsu
ID_0000	0.97573	0.759164	0.867437473
ID_0001	0.9758132	0.6540815	0.814947492
ID_0002	0.967751	0.6785036	0.823128854
ID_0003	0.9738142	0.6042942	0.789054381
ID_0004	0.9662847	0.5832143	0.774749543
ID_0005	0.9732485	0.7287234	0.850985946
ID_0006	0.9738143	0.6042942	0.789054383
ID_0007	0.9641422	0.5962546	0.780198342
ID_0008	0.9817074	0.6637867	0.822747266

Table 5: Average SSIM Values.

Table 6 displays the average Computational times of nine images produced using three different approaches. It has been observed that the proposed method outperforms other algorithms.

Image	Otsu	Multi_Otsu	SCA_Multi_Otsu
ID_0000	0.84375	5.390625	3.1171875
ID_0001	0.78125	5.515625	3.1484375
ID_0002	0.765625	6.453125	3.609375
ID_0003	0.78125	5.984375	3.3828125

ID_0004	0.8125	6.046875	3.4296875
ID_0005	0.8125	5.9375	3.375
ID_0006	0.78125	6.375	3.578125
ID_0007	1.625	5.90625	3.765625
ID_0008	0.8125	6.015625	3.4140625

Table 6: Average Computational time.

4. Conclusion

In this research, a meta-heuristic structured sine cosine method is used to optimise the Otsu objective function in computed tomography image segmentation for lung cancer. Otsu's multi-level thresholding approach is utilised as a fitness function to locate the ideal threshold values and then successfully segment the images. The suggested method therefore performs checks on a total of nine photos at different thresholds. Additionally, eight photos are subjected to Otsu, Multilevel Otsu, and Multilevel Otsu with ABC individually. Performance indicators including Peak-Signal-Noise-Ratio (PSNR), Structural Similarity Index (SSI), and Computational time are used to examine the results of four different techniques. SCA with Otsu multi-level thresholding algorithm as fitness function beats bi-level and multi-level Otsu, according to computed tomography image data for lung cancer. The application of SCA as a fitness tool may eventually extend to other multi-level thresholding techniques like Kapur's entropy. Additionally, SCA is a fundamental population-based meta heuristic algorithm that can easily be combined with other optimization algorithms to produce optimised threshold values in image segmentation, which is becoming more and more crucial in other image processing techniques like classification clustering.

5. References

Abd Elfattah M, Abuelenin S, Hassanien AE, Pan JS. Handwritten arabic manuscript image binarization using sine cosine optimization algorithm. InInternational conference on genetic and evolutionary computing 2016 Nov 7 (pp. 273-280). Springer, Cham.

Altmemi JM, Othman RR, Ahmad R, Ali AS. Implementation of sine cosine algorithm (SCA) for combinatorial testing. InIOP conference series: materials science and engineering 2020 Feb 1 (Vol. 767, No. 1, p. 012009). IOP Publishing.

Belazzoug M, Touahria M, Nouioua F, Brahimi M. An improved sine cosine algorithm to select features for text categorization. Journal of King Saud University-Computer and Information Sciences. 2020 May 1;32(4):454-64.

Dhal KG, Das A, Ray S, Gálvez J, Das S. Nature-inspired optimization algorithms and their application in multi-thresholding image segmentation. Archives of Computational Methods in Engineering. 2020 Jul;27(3):855-88.

Abd Elaziz M, Nabil NE, Ewees AA, Lu S. Automatic data clustering based on hybrid atom search optimization and sine-cosine algorithm. In2019 IEEE congress on evolutionary computation (CEC) 2019 Jun 10 (pp. 2315-2322). IEEE.

Ewees AA, Abd Elaziz M, Al-Qaness MA, Khalil HA, Kim S. Improved artificial bee colony using sine-cosine algorithm for multi-level thresholding image segmentation. Ieee Access. 2020 Feb 3;8:26304-15.

Ewees AA, Abd Elaziz M, Arafa RM, Ghoniem RM. Improved Approach Based on Fuzzy Rough Set and Sine-Cosine Algorithm: A Case Study on Prediction of Osteoporosis. IEEE Access. 2020 Nov 9;8:203190-202.

Feng Y, Zhao H, Li X, Zhang X, Li H. A multi-scale 3D Otsu thresholding algorithm for medical image segmentation. Digital Signal Processing. 2017 Jan 1;60:186-99.

Goh TY, Basah SN, Yazid H, Safar MJ, Saad FS. Performance analysis of image thresholding: Otsu technique. Measurement. 2018 Jan 1;114:298-307.

Singh N, Son LH, Chiclana F, Magnot JP. A new fusion of salp swarm with sine cosine for optimization of non-linear functions. Engineering with Computers. 2020 Jan;36(1):185-212.

Gupta S, Deep K. Hybrid sine cosine artificial bee colony algorithm for global optimization and image segmentation. Neural Computing and Applications. 2020 Jul;32(13):9521-43.

Gupta S, Deep K, Engelbrecht AP. A memory guided sine cosine algorithm for global optimization. Engineering Applications of Artificial Intelligence. 2020 Aug 1;93:103718.

Gupta S, Deep K, Mirjalili S, Kim JH. A modified sine cosine algorithm with novel transition parameter and mutation operator for global optimization. Expert Systems with Applications. 2020 Sep 15;154:113395.

Gupta S, Deep K, Moayedi H, Foong LK, Assad A. Sine cosine grey wolf optimizer to solve engineering design problems. Engineering with Computers. 2021 Oct;37(4):3123-49.

Liu W, Shi H, He X, Pan S, Ye Z, Wang Y. An application of optimized Otsu multi-threshold segmentation based on fireworks algorithm in cement SEM image. Journal of Algorithms & Computational Technology. 2018 Aug;13:1748301818797025.

Liu Y, Sun J, Yu H, Wang Y, Zhou X. An improved grey wolf optimizer based on differential evolution and OTSU algorithm. Applied Sciences. 2020 Jan;10(18):6343.

Mirjalili SM, Mirjalili SZ, Saremi S, Mirjalili S. Sine cosine algorithm: theory, literature review, and application in designing bend photonic crystal waveguides. Nature-inspired optimizers. 2020:201-17.

Mirjalili S. SCA: A Sine Cosine Algorithm for solving optimization problems." a School of Information and Communication Technology. Griffith University, Nathan Campus, Brisbane, QLD. 2016;4111.

Nenavath H, Jatoth RK. Hybrid SCA–TLBO: a novel optimization algorithm for global optimization and visual tracking. Neural Computing and Applications. 2019 Sep;31(9):5497-526.

Rosli SJ, Rahim HA, Abdul Rani KN, Ngadiran R, Ahmad RB, Yahaya NZ, Abdulmalek M, Jusoh M, Yasin MN, Sabapathy T, Andrew AM. A hybrid modified method of the sine cosine algorithm using Latin hypercube sampling with the cuckoo search algorithm for optimization problems. Electronics. 2020 Nov;9(11):1786.

Satapathy SC. Sri Madhava Raja N., Rajinikanth V., Ashour AS, and Dey N.,". Multi-level image thresholding using Otsu and chaotic bat algorithm," Neural Computing and Applications. 2016;29(12):1285-307.

8.

Sindhu R, Ngadiran R, Yacob YM, Zahri NA, Hariharan M. Sine–cosine algorithm for feature selection with elitism strategy and new updating mechanism. Neural Computing and Applications. 2017 Oct;28(10):2947-58.

Talab AM, Huang Z, Xi F, HaiMing L. Detection crack in image using Otsu method and multiple filtering in image processing techniques. Optik. 2016 Feb 1;127(3):1030-3.

Tzanetos A, Dounias G. Nature inspired optimization algorithms or simply variations of metaheuristics?. Artificial Intelligence Review. 2021 Mar;54(3):1841-62.

Yuan XC, Wu LS, Peng Q. An improved Otsu method using the weighted object variance for defect detection. Applied surface science. 2015 Sep 15;349:472-84.

Yang Q, Chu SC, Pan JS, Chen CM. Sine cosine algorithm with multigroup and multistrategy for solving CVRP. Mathematical Problems in Engineering. 2020 Mar 27;2020.

Yuan XC, Wu LS, Peng Q. An improved Otsu method using the weighted object variance for defect detection. Applied surface science. 2015 Sep 15;349:472-84.

Abd Elaziz M, Oliva D, Xiong S. An improved opposition-based sine cosine algorithm for global optimization. Expert Systems with Applications. 2017 Dec 30;90:484-500.

Bairathi D, Gopalani D (2017) Opposition-based sine cosine algorithm (OSCA) for training feed-forward neural networks IEEE 13th International Conference on signal-image technology and internet-based systems 438-444 https://doi.org/10.1109/SITIS.2017.78.

Radha Seelaboyina, Dr. Puja S Prasad, Dr. G Soma Sekhar,. 2020. "Dimensionality Reduction - Supervised and `unsupervised Approaches for Facial Recognition". International Journal of Advanced Science and Technology 29 (3), 4993 - 5001. http://sersc.org/journals/index.php/IJAST/article/view/571