

Multi-Level Thresholding for Image Segmentation on Medical Images Using Multi Otsu and Sine Cosine Optimization Algorithm

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Abstract: Image thresholding is deciding stage in many image processing algorithms. It helps to segment the image, which results in successful prediction correctly. The Sine Cosine is a meta heuristic optimization algorithm that outperforms many conventional algorithms because of its unique principle. Since lung cancer is the most deadly illness, creating a significant number of deaths worldwide, this research used lung cancer CT images. On lung cancer Computed Tomography (CT) images, this paper illustrates how to use the Otsu multi thresholding objective function and Sine Cosine nature-inspired optimization algorithms. The proposed approach uses the Otsu multi thresholding technique on a CT image as an objective function in the Sine Cosine algorithm (SCA). It aids in selecting elite solutions by measuring fitness for a given range of candidate solutions. When the Algorithm's output was evaluated using PSNR and SSIM, as well as calculation time, it was observed that the proposed approach performed higher.

Keywords: Image Segmentation, Otsu, Objective Function, Multilevel Thresholding, Sine Cosine Algorithm.

1. Introduction:

Because of their ability to offer accurate outcomes in challenging optimization tasks, nature-inspired algorithms are becoming highly popular these days. Many of the nature-inspired algorithms are meta-heuristic optimization techniques. These algorithms have the potential to increase the number of candidate solutions in the population. Cancer is one of the most severe diseases in both men and women because it is among the most leading causes of death globally. Early diagnosis increases the probability of effective treatment and survival. However, it is a time-consuming

procedure that often results in pathologists disagreeing. Early diagnosis and avoidance, on the other hand, will dramatically mitigate the chances of death. Computed Tomography (CT) images provide information to diagnose lung cancer [5]. Segmentation is a critical stage in image processing that involves separating an image into non-overlapping areas or classes. The color, texture, brightness, and contrast similarities leverage predefined procedures described as objective functions [2]. Medical images, object detection, satellite images, traffic control systems, and video surveillance benefit from camera segmentation. However, segmentation's prime objective is to transform each image into a more accurately interpreted image [6]. The study involves distinguishing homogeneous groups. One of the more well-known examples is thresholding and extensively used image processing techniques. These methods provide a threshold value, which helps differentiate foreground from background in an image. The pixel values are less than the threshold value then the area is viewed as black, and the excess qualities are viewed as white. Numerous image segmentation strategies can be employed, with the below being among the most widely known. (i) Threshold Based. (ii) Edge based. (iii) Clustering Bases. (iv) Region Based. (v) Artificial Neural Network. (vi) Partial Differential Equation. (vii) Watershed Based [2]. Thresholding techniques can be characterized into three group's namely Bi-Level thresholding, Multi-Level thresholding, and the Local Thresholding. [2]. Otsu is one of the most regularly used thresholding methods [16]. The Otsu threshold is the estimate of the mean amounts of two classes divided by this threshold. The Algorithm, in general, returns a threshold value that converts a grey scale image to a binary image. An image is represented as $I(x, y)$ with grey levels ranging from 0 to $L-1$, where L denotes distinct grey levels. Let n_i be the number of pixels with gray-level, i and n be the total number of pixels in a given image of size $M \times N$. The probability of the grey level i occurring is defined as follows [1].

$$p_i = n_i / n \quad (1)$$

If a threshold t splits an image into two groups those are D_0 and D_1 . D_0 contains pixels with levels $[0, t]$, and D_1 includes pixels with levels $[t + 1, L-1]$ [15]. $P_0(t)$ and $P_1(t)$ are the cumulative probabilities, while $\mu_0(t)$ and $\mu_1(t)$ are the mean levels of the D_0 and D_1 classes respectively [15].

$$P_0(T) = \sum_{i=1}^T p_i \quad (2)$$

$$P_1(T) = \sum_{i=T+1}^L p_i = 1 - P_0(T) \quad (3)$$

$$\mu_0(T) = \sum_{i=1}^T i \frac{p_i}{P_0(T)} = \frac{1}{P_0(T)} \sum_{i=1}^T i p_i \quad (4)$$

$$\mu_1(T) = \sum_{i=T+1}^L i \frac{p_i}{P_1(T)} = \frac{1}{P_1(T)} \sum_{i=T+1}^L i p_i \quad (5)$$

$$\sigma_0^2(T) = \sum_{i=1}^T (i - \mu_0(T))^2 \frac{p_i}{P_0(T)} \quad (6)$$

$$\sigma_1^2(T) = \sum_{i=T+1}^L (i - \mu_1(T))^2 \frac{p_i}{P_1(T)} \quad (7)$$

Let μ , $\sigma_b^2(T)$, and $\sigma_w^2(T)$ state the image's mean level, between class variance, and within class variance, respectively:

$$\mu = \sum_{i=1}^L i p_i = P_0(T) \mu_0(T) + P_1(T) \mu_1(T) \quad (8)$$

$$\sigma_b^2(T) = P_0(T) (\mu_0(T) - \mu)^2 + P_1(T) (\mu_1(T) - \mu)^2 \quad (9)$$

$$\sigma_w^2(T) = P_0(T) \sigma_0^2(T) + P_1(T) \sigma_1^2(T) \quad (10)$$

The threshold calculated by maximising the between class variance, as suggested by Otsu, is as follows:

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

This value is proportional to the threshold determined by decreasing within class variances:

$$T^* = l \leq T < L \text{ arg min}\{\sigma_w^2(T)\} \quad (12)$$

Moreover, the above threshold is about the threshold defined by minimizing the ratio of between-class variance to in-class variance [5, 6, 15, 16]. Optimization means the process of finding an elite solution to the given parameter values from all possible values to minimize or maximize the output. It is population-based, which performs based on a set of random values. SCA algorithm has two optimization stages called exploration and exploitation. The random solutions of the exploitation process are constantly changing. In the exploration phase, random variations are significantly less. The following equations are proposed for updating phases are

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

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

Where X_i^{T+1} is the current solution's position in the i^{th} dimension at t^{th} iteration, and $r_1, r_2,$ and r_3 are random numbers. P_i is the destination point's position in the i^{th} dimension, and $||$ denotes the absolute value. The above two equations are combined with being used as follows:

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

Where r_4 is a random number in the range $[0, 1]$ and r_1 is following eq.

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

Where t represents the current iteration, T represents the cumulative number of iterations, and 'a' represents the constant. Random variables $r_1, r_2, r_3,$ and r_4 are the four most essential parameters in SCA. Here, r_1 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 gives the destination random weights in order to arbitrarily emphasise ($r_3 > 1$) or deemphasize ($r_3 < 1$) the desalination effect. Finally, the r_4 parameter in eq:14 alternates between Sine and Cosine components based on random values; if the r_4 value is less than 0.5, the Sine equation is executed, and if it is greater than 0.5, the Cos equation has been executed [8, 9, 10].

2. Literature Survey:

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

2.1 Otsu Multi Threshold

Many algorithms for image recognition, object representation, and visualization start with image thresholding. They discovered the Otsu system's properties. They demonstrated that the Otsu method is equal to the mean level of two groups divided by a threshold [15]. The emphasis, according to the writers, is focused on the Otsu system. The image thresholding technique, which is based on the Monte Carlo statistical procedure, specifies that image segmentation effects depend on object context intensity difference, object size, and noise calculation but are unaffected by the object's position on the image. the proposed method can be specified as:

$$Y_b(t) = \omega P_0(t)(u_0(t))^2 + P_1(t)(u_1(t))^2 \quad (16)$$

$$\begin{aligned} \text{THv} &= \text{argmax}_{1 < t < L} Y_b(t) \\ &= \text{arg max}_{1 < t < L} (\omega P_0(t)(u_0(t))^2 + P_1(t)(u_1(t))^2) \end{aligned} \quad (17)$$

The parameter ω in eq. (16) is a weight of the object variance, with a value ranging from 0 to 1. As $P_0(t)(u_0(t))^2 + P_1(t)(u_1(t))^2$, the suggested method's threshold value is less than or equal to Otsu's threshold [16]. Considering the high-resolution 3D Otsu, a novel multi thresholding algorithm 3D Otsu and multi-scale image representation for medical image segmentation have been proposed [5]. 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 into binary using threshold values. The third step is to use the Otsu process to identify large cracks. [13].

A novel population-based Sine Cosine Optimization algorithm, which uses a mathematical model based on sine and cosine functions to generate multiple initial random candidate solutions and allows them to alternate outwards or towards the best solution. Several random and adaptive variables are mixed in this Algorithm to highlight exploration and exploitation of the search space in different optimization milestones [10]. The suggested hybrid SCA–TLBO algorithm outperforms the traditional SCA and TLBO algorithms in terms of getting away from local optima and achieving faster convergence [11]. Improved variant of SCA is called Hybrid Sine Cosine Algorithm (HSCA). It tackles the poor exploitation, skipping of existing solutions, and inadequate compromise between discovery and exploitation problems of the sine cosine algorithm. The suggested approach was tested on four engineering optimization problems, and standard and complex benchmark sets IEEE CEC 2014 and CEC 2017 [7]. SCA skips trustworthy solutions and gets stuck at sub-optimal solutions. These issues lead to premature convergence, which is terrible for evaluating global optima. Proposed novel algorithm called the memory-driven Sine Cosine Algorithm; they implemented balanced and explorative search control in SCA for candidate. To have a sufficient balance between discovery and exploitation, the number of guides in MGSCA decreases as the number of iterations rises. Meta-Heuristic Atom Search Optimization (ASO) and the Sine Cosine Algorithm, is an alternative hybrid approach for automated clustering. The fundamental goal of the proposed approach ASOSCA is to calculate the number of clusters and their centers automatically. To achieve this goal, ASOSCA employs SCA operators as a local search approach to improve ASO convergence, resulting in discovering the best solution [3]. By considering the high time complexity of the 3D Otsu algorithm, a novel thresholding algorithm for medical image segmentation using 3D Otsu and multi-scale image representation was proposed [5].

3. Methodology:

Otsu thresholding technique requires less Computational Time compared to other techniques to segment the given image. Otsu thresholding method consists of simple mathematical Sine and Cosine equations and random variables in its Algorithm to determine the best threshold value. Proposed methodology consists of five steps. (i) Giving CT images as input to Algorithm, (ii) Generating Histogram, (iii) Initializing SCA parameters, (iv) Initializing population of search agents, (v) Determining elite solution by implementing Algorithm, and repeat until terminating the condition satisfies, Figure 1 illustrates the measures taken in the suggested approach. Computed Tomography images were obtained in the first step, and in the second step, histograms were created for each image. In the subsequent stage, the parameter values of the sine cosine algorithm are initialized, followed by the population of search agents. SCA is a nature-inspired population-based

algorithm inspired by the mathematical properties of sine and cosine trigonometric functions. During the search process, SCA employs two contradictory functions. Exploration refers to the function of discovering new promising regions of the search space. At the same time, exploitation belongs to local search, which is practiced among assigned search space regions. SCA initiates the search process at random, and each candidate solution is then modified using search eq.15. Population and feasible solutions have been created randomly. The search agents' population is then initialized in the following steps by generating lower and upper bounds at random. The next step position of the search agent is to be updated. The next level is to use the Otsu objective feature to analyze the search agent. Then update the elite solution's destination position that has already been generated so far the termination condition is satisfied. When all of the steps are completed successfully, then image segmentation will be done successfully.

Steps involved in SCA Algorithm:

- Step1. Initialize a set of candidate solutions.
- Step2. Evaluate the fitness of each candidate solution.
- Step3. Initialize Parameters r_1 and t_{max} .
- Step4. Using SCA search eq.15, update each candidate solution.
- Step5. Update control parameter r_1 .
- Step6. Update the destination point x_d repeat step Four and five until the termination condition is satisfied.

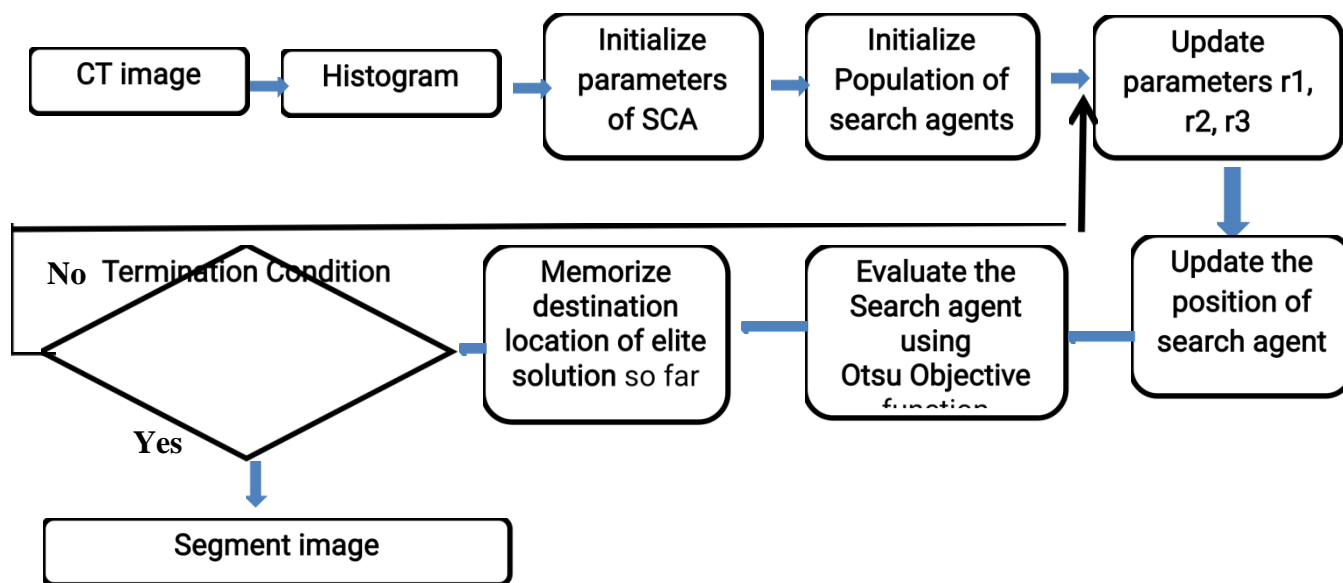


Figure 1: Proposed methodology Flow chart

3.1 Results and Discussion

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

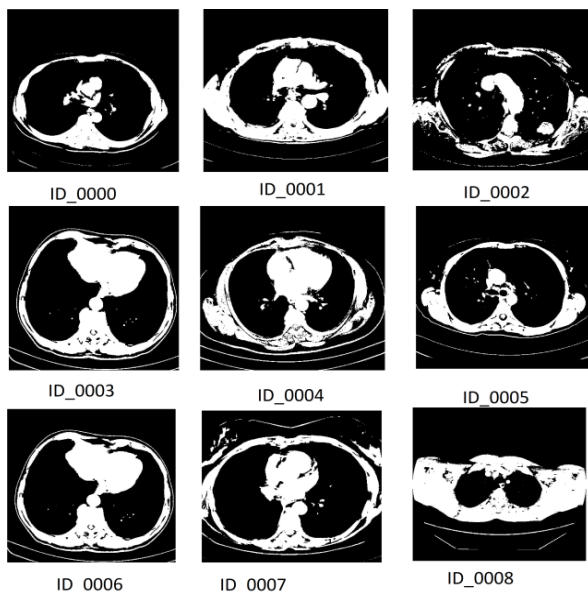


Figure 2: Input Lung Cancer CT images

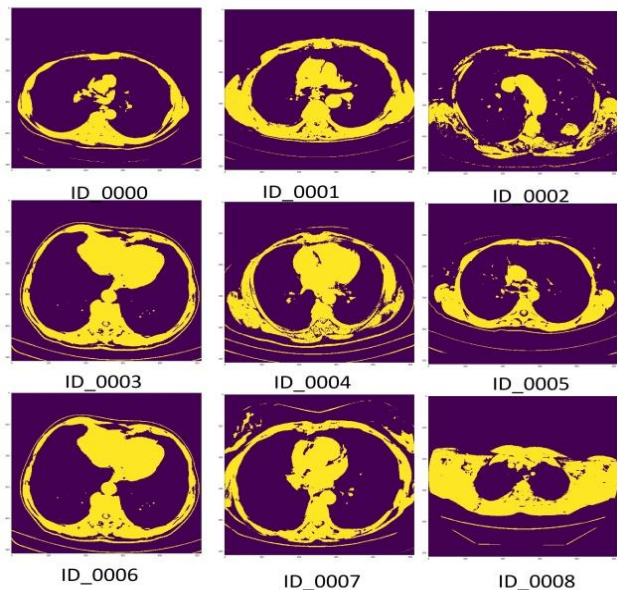


Figure 3: Output images of Otsu Image Segmentation

Figure 2 shows input images. The measurement results of experiments are given in various performance measurements such as PSNR, SSIM, and Computational Time. In this experiment, initially all of the necessary parameters are initialized. Also, the population size is equal to the number of threshold values used to segment the images, and then random variable r_1 , r_2 , r_3 , and r_4 is initialized.

3.1.1 Otsu Thresholding

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 on input images in Figure 2 and got the output as shown in Figure 3. The findings are seen in the table below, and it has been observed that the SSIM, PSNR, and CPU time are all high.

Image	SSIM	PSNR	CPU time
ID000	0.97571	35.243649	0.84375
ID001	0.9758134	34.616581	0.78125
ID002	0.967754	33.08617	0.765625
ID003	0.9738144	33.586669	0.78125
ID004	0.9662849	32.658017	0.8125
ID005	0.9732486	34.89691	0.8125
ID006	0.9738144	33.586669	0.78125
ID007	0.9641421	32.81226	1.625
ID008	0.9817076	35.566405	0.8125

Table 1: Results of Otsu Objective function

3.1.2 Multilevel Thresholding

Whenever this approach is initialized threshold values to five classes and applied to the input images, it was noticed that there is a difference in the output images and that the effects are

outstanding when comparing to Otsu thresholding. Figure 4 is an output image of multilevel thresholding.

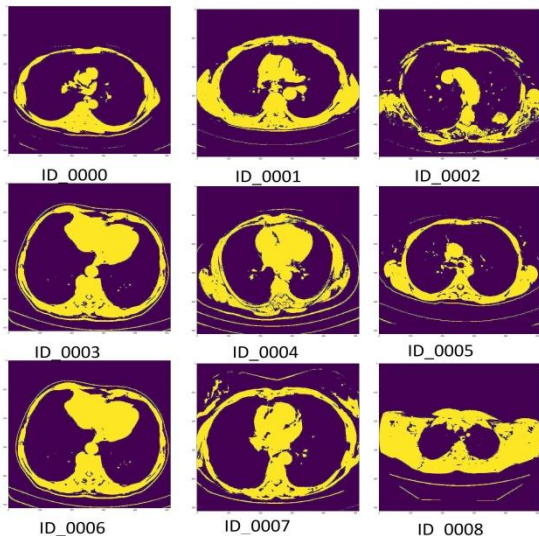


Figure 4: Multilevel Thresholding image Segmentation.

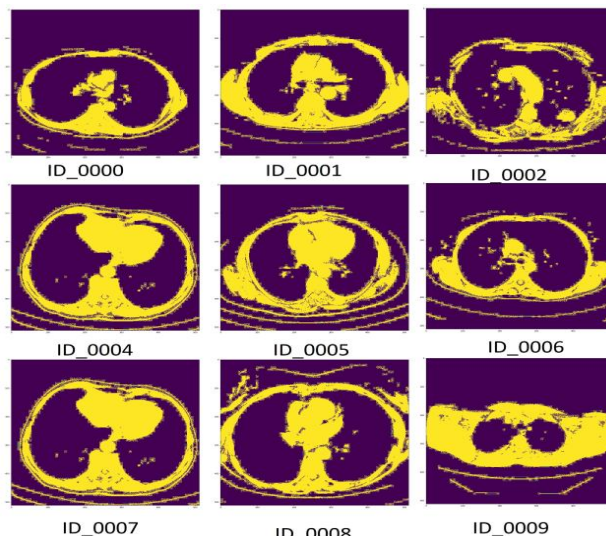


Figure 5: Output images of Sine Cosine Multi-Level Thresholding image segmentation

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

Image	SSIM	PSNR	CPU time
ID000	0.759165	39.336813	5.390625
ID001	0.6540816	37.843416	5.515625
ID002	0.6785037	37.699914	6.453125
ID003	0.6042943	37.249247	5.984375
ID004	0.5832141	36.713616	6.046875
ID005	0.7287233	38.892466	5.9375
ID006	0.6042943	37.249247	6.375
ID007	0.5962546	37.0102	5.90625
ID008	0.6637869	38.054752	6.015625

Table2: Results of Multilevel Thresholding Otsu Object function

3.1.3 SCA Multi Thresholding algorithm

Figure 1 represents the input images of Large-Scale CT lung cancer image datasets (TCIA). The proposed procedure is tested for five thresholds. 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. The proposed method outperforms the Otsu method by a substantial margin, and the multi Otsu method

Iterations	Image	SSIM	PSNR	CPU time
3	ID000	0.674985	39.345	0.296875
	ID001	0.583096	37.90722	0.28125
	ID002	0.610786	37.90307	0.46875

	ID003	0.54212	37.40899	0.640625
	ID004	0.528833	36.86227	0.609375
	ID005	0.650705	38.96742	0.28125
	ID006	0.54212	37.40899	0.28125
	ID007	0.541157	37.16821	0.28125
	ID008	0.587744	38.01257	0.28125
	Average	0.584616	37.88708	0.380208
Iterations	Image	SSIM	PSNR	CPU time
5	ID000	0.694679	39.40625	0.421875
	ID001	0.594513	37.96411	0.6875
	ID002	0.646897	37.9056	0.703125
	ID003	0.562315	37.42188	0.359375
	ID004	0.542358	36.89236	0.328125
	ID005	0.674469	38.98672	0.3125
	ID006	0.575835	37.43756	0.328125
	ID007	0.56235	37.25422	0.40625
	ID008	0.597149	38.16593	0.6875
	Average	0.605618	37.93718	0.470486
Iterations	Image	SSIM	PSNR	CPU time
7	ID000	0.707322	39.51563	0.375
	ID001	0.595951	37.97921	0.390625
	ID002	0.610786	37.93411	0.390625
	ID003	0.54212	37.54272	0.390625
	ID004	0.586924	36.92188	0.359375
	ID005	0.650705	38.98823	0.40625
	ID006	0.602358	37.45313	0.4375
	ID007	0.628684	37.29595	0.359375
	ID008	0.607223	38.21062	0.359375
	Average	0.614675	37.98238	0.385417

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

PSNR is regarded as the most valuable property for assessing the quality of image processing efficiency. Table 4 displays the observed PSNR values of input images with identical threshold values. Table 6 shows the total Computational Time..

Image	Otsu	Multi_Otsu	SCA_Multi_Otsu
ID000	35.243649	39.336813	39.42229243
ID001	34.616581	37.843416	37.95018265
ID002	33.08617	37.699914	37.91426173
ID003	33.586669	37.249247	37.45786189
ID004	32.658017	36.713616	36.89216905
ID005	34.89691	38.892466	38.98079033
ID006	33.586669	37.249247	37.43322485

ID007	32.81226	37.0102	37.23946062
ID008	35.566405	38.054752	38.12970639

Table4: Average PSNR Values.

Average PSNR values of Otsu, Multi-Level Otsu and Sine Cosine Algorithm can be represented using Figure 6.

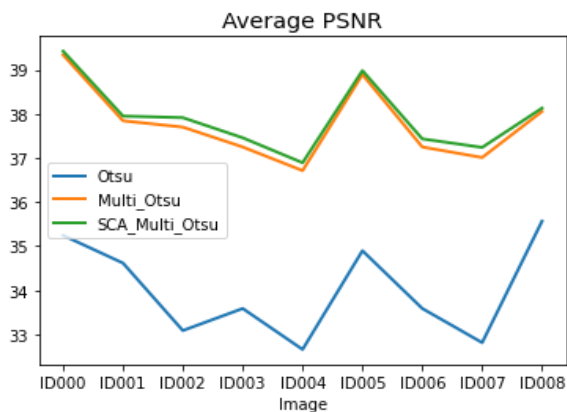
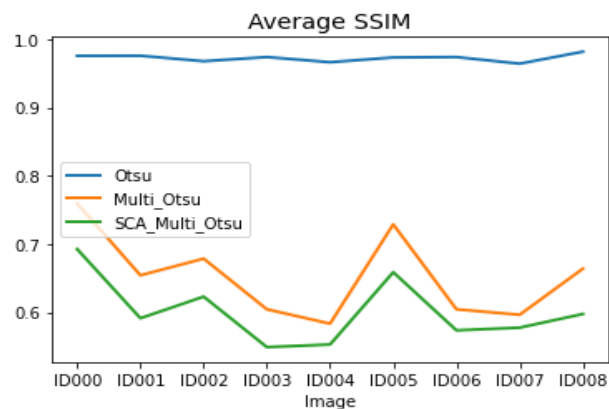
**Figure 6:** Average PSNR Line Chart**Figure 7:** Average SSIM Line Chart

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 significant margin.

Image	Otsu	Multi_Otsu	SCA_Multi_Otsu
ID000	0.97571	0.759165	0.692328532
ID001	0.9758134	0.6540816	0.591186422
ID002	0.967754	0.6785037	0.622823328
ID003	0.9738144	0.6042943	0.548851961
ID004	0.9662849	0.5832141	0.552705025
ID005	0.9732486	0.7287233	0.658626035
ID006	0.9738144	0.6042943	0.573437744
ID007	0.9641421	0.5962546	0.577396922
ID008	0.9817076	0.6637869	0.597371811

Table5: Average SSIM Values.

Figure 7 shows the representation of normal SSIM estimations of Otsu, Multi-Level Otsu and Sine Cosine Algorithm.

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

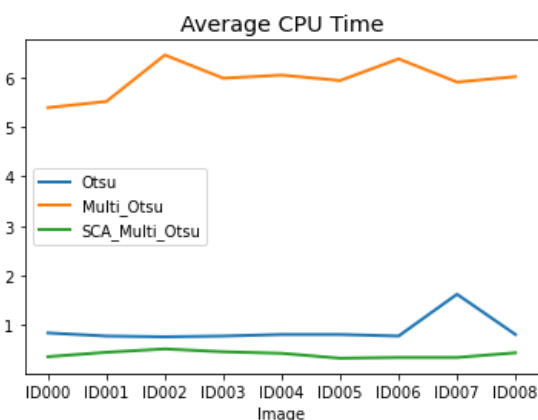
Image	Otsu	Multi_Otsu	SCA_Multi_Otsu
ID000	0.84375	5.390625	0.36458333
ID001	0.78125	5.515625	0.453125

ID002	0.765625	6.453125	0.52083333
ID003	0.78125	5.984375	0.46354167
ID004	0.8125	6.046875	0.43229167
ID005	0.8125	5.9375	0.33333333
ID006	0.78125	6.375	0.34895833
ID007	1.625	5.90625	0.34895833
ID008	0.8125	6.015625	0.44270833

Table6: Average Computational time.

Normal Computational season of Otsu, Multi-Level Otsu and Sine Cosine Algorithm can be addressed by utilizing Figure 8.

It is observed that the suggested approach takes the significant amount of time as compared to the other two methods. The proposed solution outperforms the compare to other methods, as seen in Tables 4, 5, and 6

**Figure 8:** Average CPU Time Line Chart

4. Conclusion

The Otsu objective function in lung cancer Computed Tomography image segmentation is maximized using a meta-heuristic structured Sine Cosine algorithm in this paper. Otsu's Multi-level Thresholding algorithm is used to find optimized threshold values and efficiently segment the images. As a result, the proposed approach is tested on a total of nine images at different thresholds. Furthermore, Otsu, Multilevel Otsu, and Multilevel Otsu with SCA are performed separately on nine images. The findings of these approaches are analysed using performance metrics such as Peak-Signal-Noise-Ratio (PSNR), Structural Similarity Index (SSI), and Computational Time. As per the resulted images, SCA with Otsu Multi Level Thresholding algorithm as an objective function outperforms multilevel Otsu. In the future, SCA might be used with other Multi Level Thresholding algorithms as objective function. Moreover, SCA is a meta-heuristic and population-based algorithm, it can be conveniently combined with other optimization algorithms to obtain optimized threshold values in image segmentation.

References:

- [1] J. M. Altmemi, R. R. Othman, R. Ahmad, and A. S. Ali, "Implementation of Sine Cosine Algorithm (SCA) for Combinatorial Testing," *IOP Conf. Ser. Mater. Sci. Eng.*, vol. 767, no. 1, 2020, doi: 10.1088/1757-
- [2] K. G. Dhal, A. Das, S. Ray, J. Gálvez, and S. Das, *Nature-Inspired Optimization Algorithms and Their Application in Multi-Thresholding Image Segmentation*, vol. 27, no. 3. Springer Netherlands, 2020.
- [3] M. A. Elaziz, N. Nabil, A. A. Ewees, and S. Lu, "Automatic Data Clustering based on Hybrid Atom Search Optimization and Sine-Cosine Algorithm," *2019 IEEE Congr. Evol. Comput. CEC 2019 - Proc.*, pp. 2315–2322, 2019, doi: 10.1109/CEC.2019.8790361.
- [4] A. A. Ewees, M. Abd Elaziz, M. A. A. Al-Qaness, H. A. Khalil, and S. Kim, "Improved Artificial Bee Colony Using Sine-Cosine Algorithm for Multilevel Thresholding Image Segmentation," *IEEE Access*, vol. 8, pp. 26304–26315, 2020, doi: 10.1109/ACCESS.2020.2971249.
- [5] Y. Feng, H. Zhao, X. Li, X. Zhang, and H. Li, "A multi-scale 3D Otsu thresholding algorithm for medical image segmentation," *Digit. Signal Process. A Rev. J.*, vol. 60, pp. 186–199, 2017, doi: 10.1016/j.dsp.2016.08.003.
- [6] 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, no. March 2017, pp. 298–307, 2018, doi: 10.1016/j.measurement.2017.09.052.
- [7] S. Gupta and K. Deep, "A novel hybrid sine cosine algorithm for global optimization and its application to train multilayer perceptrons," *Appl. Intell.*, vol. 50, no. 4, pp. 993–1026, 2020, doi: 10.1007/s10489-019-01570-w.
- [8] S. Gupta, K. Deep, S. Mirjalili, and J. H. Kim, "A modified Sine Cosine Algorithm with novel transition parameter and mutation operator for global optimization," *Expert Syst. Appl.*, vol. 154, 2020, doi: 10.1016/j.eswa.2020.113395.
- [9] S. M. Mirjalili, S. Z. Mirjalili, S. Saremi, and S. Mirjalili, *Sine cosine algorithm: Theory, literature review, and application in designing bend photonic crystal waveguides*, vol. 811. Springer International Publishing, 2020.
- [10] S. Mirjalili, "SCA: A Sine Cosine Algorithm for solving optimization problems," *Knowledge-Based Syst.*, vol. 96, pp. 120–133, 2016, doi: 10.1016/j.knosys.2015.12.022.
- [11] H. Nenavath and R. K. Jatoth, "Hybrid SCA–TLBO: a novel optimization algorithm for global optimization and visual tracking," *Neural Comput. Appl.*, vol. 31, no. 9, pp. 5497–5526, 2019, doi: 10.1007/s00521-018-3376-6.
- [12] S. C. Satapathy, N. Sri Madhava Raja, V. Rajinikanth, A. S. Ashour, and N. Dey, "Multilevel image thresholding using Otsu and chaotic bat algorithm," *Neural Comput. Appl.*, vol. 29, no. 12, pp. 1285–1307, 2018, doi: 10.1007/s00521-016-2645-5.
- [13] A. M. A. Talab, Z. Huang, F. Xi, and L. Haiming, "Detection crack in image using Otsu method and multiple filtering in image processing techniques," *Optik (Stuttg.)*, vol. 127, no. 3, pp. 1030–1033, 2016, doi: 10.1016/j.ijleo.2015.09.147.
- [14] C. C. Y. Rao, E. Mahender, and G. Geetha, "Preprocessing algorithm for computational privacy protection in data mining," *J. Adv. Res. Dyn. Control Syst.*, vol. 10, no. 8, pp. 265–272, 2018.
- [15] X. Xu, S. Xu, L. Jin, and E. Song, "Characteristic analysis of Otsu threshold and its applications," *Pattern Recognit. Lett.*, vol. 32, no. 7, pp. 956–961, 2011, doi: 10.1016/j.patrec.2011.01.021.
- [16] X. C. Yuan, L. S. Wu, and Q. Peng, "An improved Otsu method using the weighted object variance for defect detection," *Appl. Surf. Sci.*, vol. 349, pp. 472–484, 2015, doi: 10.1016/j.apsusc.2015.05.033.

- [17] X. C. Yuan, L. S. Wu, and Q. Peng, “An improved Otsu method using the weighted object variance for defect detection,” *Appl. Surf. Sci.*, vol. 349, pp. 472–484, 2015, doi: 10.1016/j.apsusc.2015.05.033.
- [18] Asraf Yasmin, B., Latha, R., & Manikandan, R. (2019). Implementation of Affective Knowledge for any Geo Location Based on Emotional Intelligence using GPS. *International Journal of Innovative Technology and Exploring Engineering*, 8(11S), 764–769. <https://doi.org/10.35940/ijitee.k1134.09811s19>
- [19] D. R. S. . et. al., “ESTIMATING THE EFFICIENCY OF MACHINE LEARNING IN FORECASTING HARVESTING TIME OF RICE”, *IJMA*, vol. 10, no. 2, pp. 1930 - 1937, Apr. 2021.