Improved OTSU Theory of Image Multi-Threshold Segmentation by Incorporating Ant Colony Algorithm

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In today's information age, people have higher requirements for image processing and classification and are increasingly concerned about the topic of multi-threshold image segmentation. In recent years, with the continuous development of computer technology and its theoretical basis, the relevant research direction gradually towards a more accurate and efficient direction. It is an algorithm that have both global and localized characteristics and can deal with dynamic changes in uncertain environments. This study introduces the enhanced OTSU theory and analyzes the improved multi-threshold image segmentation which is based on the information entropy and greedy factor and other related algorithms to segment the image, and can achieve two goals under this model: one is to maximize the grey value; the other is the optimal path. The author first analyzes the aging routes of ants and other experimental data and finds that there is not much discrepancy. Secondly, he finds a new method to reduce the competition between ant colonies and also reduce the noise pollution level, thus improving the overall performance and convergence speed.

Povzetek: Članek predstavi izboljšano OTSU teorijo za večpragovno segmentacijo slik, ki vključuje algoritem kolonije mravelj. Predlagana metoda poveča natančnost in hitrost segmentacije s kombinacijo optimizacije mravelj in OTSU analize histogramov, kar izboljša prepoznavanje večpragovnih slik v različnih aplikacijah.

1 Introduction

Otsu theory has certain advantages in image segmentation, but there are also some shortcomings: on the one hand, because the method introduces a small and unstable amount of information, not easy to deal with noise and other defects leading to its inability to be applied to real-life scenes; on the other hand, although the improved algorithm overcomes the traditional ant colony algorithm for the same problem when there are different thresholds to choose different effects, still based on a single individual and although the improved algorithm overcomes the different effects of the traditional ant colony algorithm when selecting different thresholds for the same problem, it is still a difficult problem that cannot be solved by target detection and multi-stage search based on individual ant features [1-3].

Multi-threshold segmentation is a new image processing technique based on mathematical theory and computer graphics, which is based on the rational selection and optimization of objective functions and constraints. Although much progress has been made in the application of multi-threshold segmentation in image classification, there are still some problems: the experimental algorithm does not take into account the boundary conditions such as the amount of information and grey level changes between the target and the background [5-6]. Since the background is a feature of different regions in real situations, it is impossible to determine a suitable size range for comparison; at the same time, the image segmentation results of the three vertices of the target contour edge, edge, and bottom map obtained after binarization may also produce certain differences, thus leading to deviations in the segmentation effect.

In the 1990s, domestic research on the fusion threshold segmentation algorithm began. First, some foreign scholars proposed and conducted experiments to verify that the method can effectively improve image quality and enhance imaging accuracy [7]; second, based on improved Otsu theory combined with Otsu theory to establish a concept model based on "multiple thresholds", "group-type coefficients The second is to establish a conceptual model based on "multiple thresholds" and "group-type coefficients" to realize the extraction of information about the distance change between the target pixel and the background based on the improved Otsu theory [8] proposed a combined thresholding method for image processing, which improves the search efficiency in the target region by removing the noise. To address the traditional artificial grey-scale histogram blindly extracting features from the problem to achieve a new method of bilateral or multi-way cluster analysis, and used genetic algorithms to solve dynamic stochastic process parameter combination weights to obtain the global optimal solution with local optimal control effect [9].

In the development of image segmentation techniques, the main focus is on the analysis of the objective function to obtain a complete, effective, and realistic model of the system, a method that can be a good solution to the problems faced [10]. However, this method does not take into account the complex phenomena such as local optimal solutions and noise pollution arising from the influence of image greyscaling and topology, which makes it difficult to be widely used and promoted. The ant colony technique is computationally heavy and redundant, and the thresholds found are not global, making the algorithm somewhat unstable [11]. Therefore, it is improved by introducing the particle swarm algorithm into the ant colony algorithm and improving the fitness formula to achieve a fast, efficient, and accurate search for the best threshold, and also to effectively avoid the improved algorithm falling into a local optimum.

2 Related works

Table 1 depicts the comparison of previous studies.

Table 1: Summary table in related work

Ref	Objective	Method	Limitation	Result
[12]	Addressing noise interference and over-segmentation in current techniques is crucial for improving the accuracy of identifying diseases in maize foliar pictures.	The complete particle swarm optimization (PSO) technique has been enhanced with a revolutionary elite approach to improve segmentation accuracy and optimal segmentation threshold.	This method demonstrated enhanced segmentation efficiency, but it may face challenges in situations with unpredictable illness patterns or intricate environmental factors affecting picture quality.	Experiments showed improved segmentation results compared to current algorithms on maize foliar disease photos, indicating the convergence and stability of the suggested method.
[13]	The development of a multi-threshold image segmentation approach aims to enhance the quality of medical image processing for more accurate diagnosis judgments.	Create a horizontal and vertical crossover search ensemble multi-strategy-driven shuffled frog leaping algorithm (HVSFLA).	The effectiveness of HVSFLA is significantly influenced by the quality of the original population and the configuration of its parameters, particularly in complex segmentation jobs or noisy photos.	The experimental data reveals that HVSFLA outperforms other algorithms in terms of resilience and segmentation accuracy, indicating its potential for medical image segmentation applications.
[14]	To accelerate convergence and prevent local optima, provide an enhanced particle swarm optimization algorithm-based OTSU multi-threshold picture	Employ a new method to compute particle contribution degrees, utilize asynchronous monotone learning factors to balance local and global search, and apply chaotic	The intricacy of the picture data and the choice of parameters can affect how effective the procedure is.	The proposed algorithm outperforms existing methods in segmentation accuracy, efficiency, and

	segmentation technique.	optimization to account for population variability.		calculation times by 30%, demonstrating superiority over classic meta-heuristic algorithms.
[15]	To improve segmentation accuracy and efficiency, presented a hybrid whale optimization-based two-dimensional Otsu multi-threshold image segmentation method.	The Otsu single-threshold technique will be expanded to two dimensions for multi-threshold segmentation, and a hybrid whale optimization technique will be implemented for improved accuracy.	The suggested method's effectiveness may vary based on image parameters and attributes, and in some instances, computational complexity may still pose a challenge.	The suggested approach outperforms conventional methods in segmentation efficiency and quality, surpassing Otsu multi-threshold segmentation in one dimension, as shown by PSNR and SSIM assessments.
[16]	Reduce computing complexity, sluggish convergence, and premature convergence in current approaches to increase the precision of multi-threshold picture segmentation.	The Adaptive Perturbation of Oscillation and Mutation Operation (AFOA-APM) Aptenodytes Forsteri Optimization Algorithm is suggested.	Despite the enhancements, AFOA-APM may still encounter challenges with intricate photos or situations with uneven illumination.	AFOA-APM outperforms existing methods in quality, consistency, and accuracy, as demonstrated by CEC 2017 benchmarks and picture segmentation tasks, effectively addressing multi-threshold segmentation challenges.
[17]	A meta-heuristic equilibrium technique is being developed to enhance research quality and analysis by determining optimal thresholds in grayscale pictures for improved image segmentation accuracy.	A unique meta-heuristic equilibrium technique was used to determine ideal threshold values using images from the Berkeley Segmentation Dataset, comparing performance against seven well-known techniques.	This approach, despite excelling in greater levels of threshold can result in decreased average deviations and CPU time for fitness values, peak signal-to-noise ratio, and structural resemblance score.	The new algorithm demonstrated superior performance in various criteria, including structural similarity index, maximum absolute error, peak signal-to-noise ratio, and fitness values, enhancing picture segmentation.
[18]	The study compares the effectiveness of AGDE, an enhanced Differential Evolution algorithm, with more advanced and	With Rényi's entropy and a non-local mean 2D histogram, use AGDE in MTIS. Examine using the TPC and BSDS500	Insufficient examination of various datasets and scant discourse on computational	The AGDE-based segmentation approach, despite its superior performance

	conventional methods in multi-threshold image segmentation, particularly for medical images.	datasets.	complexity.	compared to its competitors, has the potential to enhance the accuracy and reliability of medical picture segmentation.
[19]	The use of an improved Whale Optimization Algorithm (LCWOA) has been utilized to enhance the quality of skin cancer picture segmentation and aid in disease detection.	The WOA to enhance optimization speed, promote exploration, and verify CEC2014 functionality for skin cancer image segmentation.	The study focused on the performance comparison of WOA variations, specifically skin cancer pictures, and did not investigate its applicability beyond threshold segmentation.	LCWOA outperforms current WOA variations in optimizing skin cancer images, enhancing efficiency, accuracy, and velocity, thus improving patient care and disease identification.

3 Methods and materials

3.1. Ant colony optimization algorithm

The algorithm Ant colony optimization algorithm (ACO) is a meta-heuristic. Ants take the shortest route possible to locate food and get back to their colony, just as in real life. Ants employ pheromone trails to retrace their routes. In ACO, pheromones and fake ants are created to find the shortest path across a graph. Since pheromone evaporates, the ants will go along the path with the highest concentration of pheromone. ACO first constructs an initial solution from a finite set of solution components, just as in previous algorithms. The ant then proceeds to move down the graph, where each vertex denotes a component of the solution. The ACO was first proposed to be applied to the traveler's problem, There are n cities, the city i can be represented by a pair of real numbers (xi,yi) and its coordinates, and city j is represented by (xj,yj), then the distance between city i and city j is can be found by the following equation.

$$d_{ij} = \sqrt{\left(x_i - x_j\right)^2 + \left(y_i - y_j\right)^2} \tag{1}$$

Then at moment t, the transfer probability P of choosing path dij is

$$P_{ij}^{k}(t) = \begin{cases} \dfrac{\tau_g^{\alpha}(t)\eta_j^{\beta}(t)}{\sum_{stationdstationd}^{\alpha}(t)\eta_a^{\beta}(t)}, & j \in allowed_k \\ 0 & otherwise \end{cases} \tag{2}$$

The enlightening function mentioned above is

$$\eta_{ij} = \frac{1}{d_s} \tag{3}$$

To avoid a situation where the amount of pheromone gradually disappears and too much residual pheromone overwhelms the heuristic information, after a traversal visit to all cities, the algorithm has to do a global pheromone update for this traversal, which is given by the following equation.

$$\tau_{ij}(t+n) = (1-\rho)\tau_{ij}(t) + \Delta\tau_{ij}(t, t+n) \tag{4}$$

The expression for the pheromone increment is:

$$\Delta\tau_{ij}(t, t+n) = \sum_{k=1}^{m} \Delta\tau_{ij}^{k}(t, t+n) \tag{5}$$

Under the ant-perimeter system model, ant-density system model, and ant-volume system model, the solution procedure for the parameters in equation (5) is as follows (6) (7) (8), respectively.

$$\Delta\tau_{ij}(t, t+n) = \begin{cases} \frac{Q}{L_k} \\ 0, & otherwise \end{cases} \tag{6}$$

$$\Delta\tau_{ij}(t, t+n) = \begin{cases} \text{Q} \\ 0, & otherwise \end{cases} \tag{7}$$

$$\Delta\tau_{ij}(t, t+n) = \begin{cases} \frac{Q}{D_{ij}} \\ 0, & otherwise \end{cases} \tag{8}$$

The difference between the two is the different information emphasized. The flowchart of the steps of the ant colony algorithm on the TSP problem is shown in Figure 1.

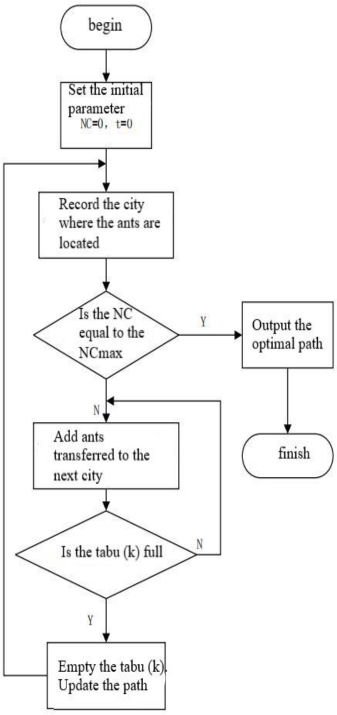

Figure 1: Flowchart of the ant colony algorithm on TSP

3.2. Otsu algorithm

The total number of pixels in an image is represented by n. It is obvious that n has the following formula (9),

$$n = n_1 + n_2 + \cdots + n_L \quad (9)$$

For each ni, the probability of its occurrence in the total number n is fi, then

$$f_i = \frac{n_i}{n} \quad （10）$$

$$\sum_{i=0}^{L-1} f_i = 1 \quad （11）$$

Using the grey value i to partition the image into two classes, foreground, and background, represented using G_0 G_1 respectively, that is, (12), then define the proportion of pixels in these two classes G_0 and G_1 to be ω_0 and ω1.

$$G_0 = \{0,1,2,\cdots,t\}, G_1 = \{t+1, t+2,\cdots, L-1\} \quad （12）$$

$$\omega_0 = \sum_{i=0}^{1} f_i \quad （13）$$

$$\omega_1 = \sum_{i=ai+1}^{L-1} f_i \quad （14）$$

Assuming that ω_0 is ω1, then there is (15) and the total mean of the image is represented using μT

$$\omega_1 = 1 - \omega_0 \quad （15）$$

$$\mu_0 = \sum_{i=0}^{i} \frac{if_i}{\omega_0} = \frac{T}{\omega_0} \quad （16）$$

$$\mu_1 = \sum_{i=r+1}^{L-1} \frac{if_i}{\omega_1} = \frac{\mu_r - T}{\omega_1} \quad （17）$$

$$\mu_T = \sum_{i=0}^{L-1} if_i = \omega_0\mu_0 + \omega_1\mu_1 \text{ ,} \quad T = \sum_{i=0}^{r} if_i \quad （18）$$

The variances are respectively :

$$\sigma_0^2 = \sum_{i=0}^{i} \frac{(i-\mu_0)^2 f_i}{\omega_0} \quad （19）$$

$$\sigma_1^2 = \sum_{i=i+1}^{L-1} \frac{(i-\mu_1)^2 f_i}{\omega_1} \quad （20）$$

$$\sigma_b^2 = \omega_0(\mu_0 - \mu_T)^2 + \omega_1(\mu_1 - \mu_T)^2 \quad （21）$$

$$\sigma_w^2 = \omega_0\sigma_0^2 + \omega_1\sigma_1^2 \quad （22）$$

$$t_{qut} = Max_b\{\sigma_b^2(t)\} \quad （23）$$

$$t_{qet} = Min_{0\le t\le L-1}\{\sigma_w^2(t)\} \quad （24）$$

$$\sigma_b^2 = \omega_1\omega_2(\mu_0 - \mu_1)^2 = \frac{[T-\mu_T\omega(t)]^2}{\omega(t)[1-\omega(t)]} \quad （25）$$

Assuming that an image has a grayscale of L, the total number of pixels of the image can be expressed as:

$$N = \sum_{i=0}^{L-1} n_i \quad （26）$$

$$f_i = \frac{n_i}{N} \quad （27）$$

For the multi-threshold Otsu algorithm, assuming that the image is to be segmented into n classes, it is obvious that there can be a total of n-1 segmentation thresholds to segment the image into n different classes. Let us assume that these n thresholds are denoted as T1, T2,..., Tn-1,n classes are obtained by segmenting the image using n-1 thresholds, and for these n classes, the probability of occurrence of the total pixels in each class is assumed to be F1, F2,... ,Fn-1,where.

$$F_k = \sum_{i=T_k}^{T_{i+1}-1} f_i \quad （28）$$

$$\mu_k = \frac{1}{F_k}\sum_{i=T_k}^{T_{k+i}-1} if_i \quad （29）$$

$$\sigma_k^2 = \sum_{i=T_k}^{T_{k+1}-1} (i-\mu_k)^2 \frac{f_i}{F_k} \quad （30）$$

The mean grey value of the image, the inter-class variance, and the intra-class variance of each class are

$$\mu = \sum_{i=0}^{L-1} if_i \quad （31）$$

$$\sigma_b^2 = \sum_{i=0}^{n-1} F_i(\mu_i - \mu)^2 \quad （32）$$

$$\sigma_w^2 = \sum_{i=0}^{n-1} F_i\sigma_i^2 \quad （33）$$

Multi-threshold Otsu optimal threshold should follow the same principle, and the largest or smallest set of thresholds is the multi-threshold Otsu optimal threshold.

4 Improved OTSU theory of image multi-threshold segmentation incorporating ant colony algorithm

4.1 Main principles of the improved 3D OTSU algorithm

The three-dimensional OTSU method is first optimized using the ant colony algorithm. The resulting suboptimal solution is then optimized using the chaos method. The improved algorithm captures the global nature more and avoids local extremes. The chaos optimization algorithm reflects the computational process of the algorithm as a search process for chaotic trajectories. To obtain a sizable partitioning effect, the given function variables are linearly mapped in the interval [0, 1]. In this paper, a logistic mapping is used which is simple in principle. The algorithm is mapped into chaotic sequence variables for all but the best solution by the following equation.

$$x_{k_0+1} = \mu * x_{k_0}(1 - x_{k_0}) \quad (34)$$

$$X = (x_1, x_2, \cdots, x_D), X(k_0) = (x_1^{k0}, x_2^{k0}, \ldots, x_D^{k0}) \quad (35)$$

The main steps of the chaos optimization method are as follows.

(1) Initialization

Let

$$k_0 = 0, X(k_0) = X(0), x^* = X(0), f(x^*) = f(X(0)) \quad (36)$$

Transform the optimization variables into chaotic variables h within 0 to 1 according to the following formula.

$$hx_j^{k0} = \frac{x_j^{k0} - x_j^{min}}{x_j^{max} - x_j^{min}} \quad (37)$$

(2) Calculate the chaotic variables for the next iteration

Transform h into the chaotic variables for the next iteration according to the following equation:

$$hx_j^{k0+1} = \mu hx_j^{k0}(1 - hx_j^{k0}) \quad (38)$$

(3) Solving for the optimization variables

Translate h into the optimization variables according to the following equation:

$$x_j^{k0+1} = x_j^{min} + hx_j^{k0+1}(x_j^{max} - x_j^{min}) \quad (39)$$

(4) Performance comparison

Compare the performance of the resulting new solution by optimizing the variables.

$$x^{(k0+1)} = (x_1^{k0+1}, x_2^{k0+1}, \ldots, x_j^{k0+1}, \ldots, x_D^{k0+1}) \quad (40)$$

(5) Solution update

If the new solution is better, then we have (41), otherwise, x* remains unchanged.

$$x^* = x^{(k0+1)} \quad (41)$$

(6) Output results

Output x* when the maximum limit of chaotic searches is reached, otherwise return to step (2). The flow chart is shown below in Figure 2.

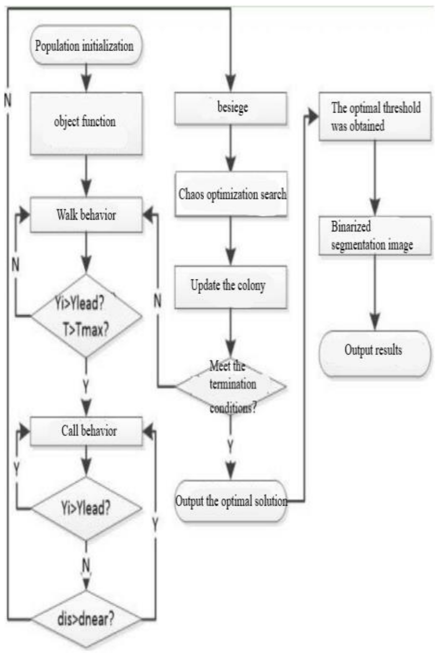

Figure 2: Flow chart of the improved 3D OTSU method algorithm

The paper suggests a unique method for image multi-threshold segmentation by merging ACO with Otsu's method. The advantages of both approaches are combined in this integration: Otsu's approach uses histogram analysis to effectively choose the best thresholds, and ACO offers strong optimization possibilities. The suggested strategy improves convergence characteristics and segmentation accuracy by combining various techniques. It has potential uses in several domains where accurate segmentation is essential, such as medical imaging and remote sensing. It could prove to be a useful tool for image analysis problems involving multi-threshold segmentation with more testing and improvement.

4.2 Simulation experiments and analysis of results

Dataset 1: For fingerprint image 1 and fingerprint image 2, the original fingerprint image is relatively clear, and the segmentation results obtained by both algorithms are also clearly visible. For fingerprint image 3, the image of the bottom of the stripe is slightly blurred, resulting in an average segmentation result shown in Figure 3. In general, however, the fingerprint pattern is segmented by both algorithms.

Figure 3: Fingerprint image segmentation results

Dataset 2: This paper [20] makes use of the colonoscopy tissue segment data set from the Bio-Medical Grand Challenge. Out of 93 complete slide pictures of whole slide imaging (WSI), 250 images with an average size of 5000 × 5000 pixels are included in the data set. The study creates a binary mask, where 255 represent the malignant tumor and 0 represents the backdrop.

One of the drawbacks of the traditional thresholding method is that it does not accommodate multiple thresholding of the image. Table 1 below compares the regional consistency and runtime results of the two segmentation algorithms. Table 1 shows that the difference in time is not significant, but the regional consistency is significantly higher. The simulation proves that the DP artificial neural network with a combination of integrated whole-amplitude and bilateral filtering can effectively improve the problem of distributing the number of ants and the total energy concentration in the target region (i.e. the threshold can be well expressed when the number of particles exceeds a certain value in the same dimension). The improved algorithm introduces a chaotic local search algorithm to make the obtained thresholds more accurate. Therefore, the improved algorithm proposed in this paper can be used as a practical method for segmenting fingerprint images.

Table 1: Results of fingerprint image runs

Picture	Particle swarm optimization by the 3 D OTSU method		The algorithm in this paper	
	Regional consistency	time (ms)	Regional consistency	time (ms)
Picture1	0.942	605	0.947	600
Picture2	0.986	611	0.995	594
Picture3	0.963	463	0.980	460

4.3. Comparison result

The key processes have been developed using the Python 3.11.4 environment. The suggested optimization techniques were tested in a simulated environment using a Windows 11 laptop equipped with an Intel i5 11th Gen CPU and 32 GB of RAM. This study used OTSU-ACO approaches for image multi-threshold segmentation to analyze data. In OTSU-ACO identification tasks, numerous statistics are utilized to measure a model's prediction capabilities, including Accuracy, f-measure, Sensitivity, Specificity, and Computational time. Particle swarm optimization (PSO) [20], Darwinian particle swarm optimization (DPSO) [20], and fractional order Darwinian particle swarm optimization (FODPSO) [20], One-dimensional OTSU [21], Two-dimensional OTSU [21], 2D OTSU-GA [21] were compared with our proposed method. Table 2 represented the overall comparison of the proposed method.

Table 2: Outcomes of Accuracy, Sensitivity, F-Measure, Specificity

Methods	**Accuracy**	**Sensitivity**	**F-Measure**	**Specificity**
PSO [20]	0.76	0.77	0.55	0.72
DPSO [20]	0.86	0.86	0.66	0.85
FODPSP [20]	0.89	0.86	0.68	0.87
OTSU-ACO [Proposed]	0.96	0.94	0.95	0.94

Accuracy: The accuracy with which pixels are accurately classified into several intensity levels is referred to as picture multi-threshold segmentation accuracy. It gauges how well-split areas and ground truth accord. Accurately classifying pixels into intensity levels is measured by segmentation accuracy, which is important for many image processing applications such as object identification and medical imaging. Figure 4 shows the comparison of accuracy.

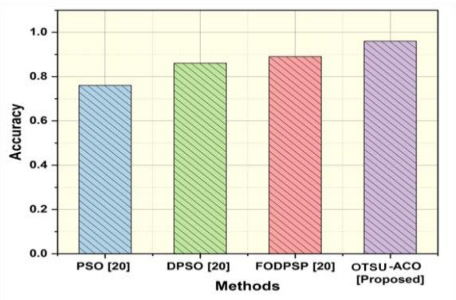

Figure 4: Outcome of accuracy

The suggested OTSU-ACO approach achieves a better accuracy of 0.96, outperforming other methods like PSO, DPSO, and FODPSP.

Sensitivity: Sensitivity quantifies the percentage of real positives that a segmentation model accurately identifies. It is essential for determining accuracy. View a multi-threshold segmentation example. Using intensity thresholds as a guide, multi-threshold segmentation separates a picture into many areas. It's helpful for precisely extracting items with different grayscale values. Figure 5 shows the comparison of sensitivity.

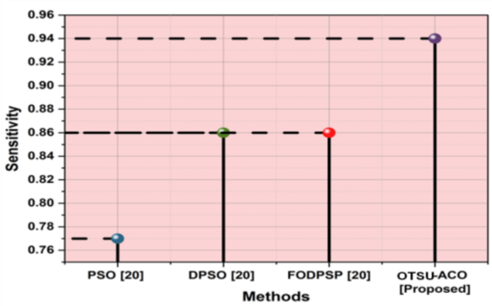

Figure 5: Outcome of sensitivity

In comparison to the other methods under comparison, the suggested OTSU-ACO approach has the maximum sensitivity of 0.94, outperforming the values of 0.77, 0.86, and 0.86 for PSO, DPSO, and FODPSP, respectively.

F Measure: The F-measure, which combines precision and recall, is a statistical indicator of test accuracy. To assess segmentation algorithms, it offers a single score that strikes a balance between these two measures. Figure 6 shows the comparison of F-measure.

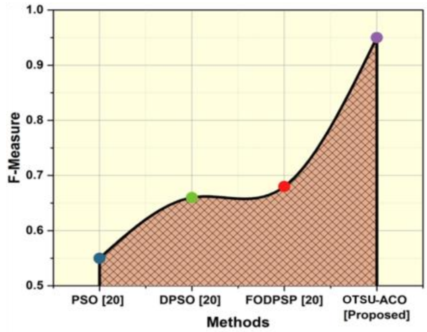

Figure 6: Outcome of F-Measure

With an F-Measure of 0.95, the suggested OTSU-ACO approach outperforms PSO, DPSO, and FODPSP, which had scores of 0.55, 0.66, and 0.68, respectively.

Specificity: The capacity of a segmentation algorithm to precisely detect true negatives is referred to as specificity. Multi-threshold segmentation needs to discern various items in a picture according to their intensity levels. Figure 7 shows the comparison of Specificity.

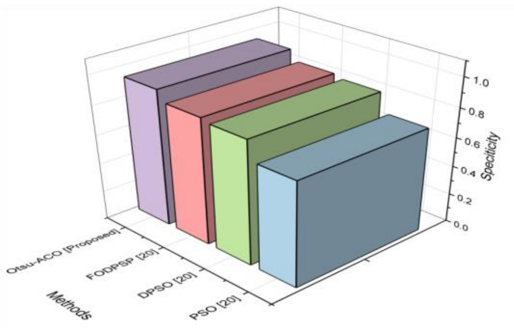

Figure 7: Outcome of specificity

With a specificity score of 0.94, the suggested OTSU-ACO approach outperforms the other methods that were tested, with scores of 0.72, 0.85, and 0.87 for PSO, DPSO, and FODPSP, respectively.

Computation time: The amount of time needed for a computer or algorithm to do a task is referred to as computational time. By dividing an image according to many intensity thresholds, a technique known as multi-threshold segmentation makes it easier to separate and analyze objects. Table 3 and Figure 8 show the computation time outcome.

Table 3: Comparison of computational time

Computational Time	No of images		
	1	**2**	**3**
One-dimensional OTSU [21]	8.236	7.994	8.727
Two-dimensional OTSU [21]	12.1534	12.967	12.071
2D OTSU-GA [21]	10.241	11.692	11.734
OTSU-ACO [Proposed]	6.235	6.348	7.259

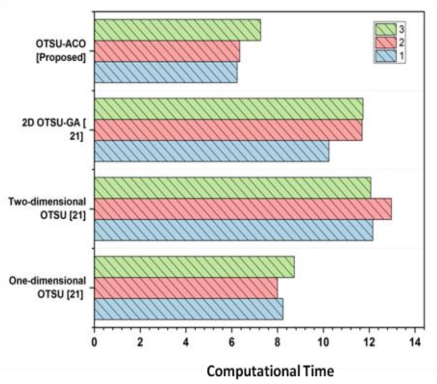

Figure 8: Outcome of computational time

The one-dimensional OTSU, two-dimensional OTSU, and two-dimensional OTSU-GA image segmentation approaches have computing times ranging from around 7.994 to 12.967 seconds. The effectiveness of the suggested OTSU-ACO approach is enhanced, with timings ranging from 6.235 to 7.259 seconds.

5 Discussion

Multi-threshold segmentation techniques are essential in many domains, from agricultural disease detection to medical imaging. These researches showcase LCWOA strategies [18] for addressing issues like computational complexity and noise interference, such as multi-strategy ensembles and improved optimization methods. Notwithstanding these drawbacks, they show encouraging improvements in efficiency and accuracy, which are essential for accurate segmentation and diagnosis. Existing techniques such as (PSO) [20], (DPSO) [20], and (FODPSO) [20] have the following drawbacks: they are inefficient in handling large optimization landscapes, sensitive to parameter choices, and converge to local optima. These restrictions may result in less-than-ideal segmentation outcomes and higher computing expenses. By combining ACO for global optimization with Otsu's approach, which automatically generates appropriate thresholds, the suggested OTSU-ACO technique overcomes these shortcomings. The approach improves the segmentation robustness and accuracy by utilizing Otsu's efficiency in threshold selection and ACO's capacity to investigate a variety of solutions. It also improves adaptation to complicated picture properties and lessens susceptibility to parameter adjustments, which leads to better segmentation performance. This technique produces accurate segmentation results in a multi-threshold segmentation situation by iteratively adjusting threshold values depending on the image intensity distribution. This effectively divides an image into discrete sections.

6 Conclusion

In this thesis, take the threshold selection in the experiment as the research content, combine the research results of domestic and foreign scholars on image multi-threshold segmentation algorithm, work from the improved Otsu theory in moving average filter peak detection and recognition, fusion and model, etc., by proposing a new threshold segmentation method to achieve image multi-smoothing, and extend it to the image. In this paper, the main focus is on the segmentation and study of images based on an improved algorithm. In this paper, Otsu theory is used as a fusion of ant colony algorithm and thresholding to obtain the objective function. Firstly, the principle and implementation process is introduced, and a new idea of "multimodal", is proposed to deal with the constraints and boundary conditions, the optimal solution for noise pollution, and can improve the convergence characteristics, finally verify the effect and advantages, and finally draw the conclusion that the improved algorithm has good performance. Even though the suggested approach appears to be enhancing image segmentation, more research is necessary to determine whether it can be applied in practical settings and scaled to bigger datasets. Future studies may also look into using deep learning methods for improved efficiency and accuracy in segmentation across a range of imaging applications.

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