Hybrid Optimization Algorithm for Multi-level Image Thresholding Using Salp Swarm Optimization Algorithm and Ant Colony Optimization

K. Manikandan[1,*] and B. Sudhakar[2]
[1] Department of Electronics and Communication Engineering, Government College of Engineering, Thanjavur, India
[2] Department of Electronics and Communication Engineering, Annamalai University, Chidambaram, India
Email: maniecegcetj@gmail.com (K.M.), balrajsudhakar@gmail.com (B.S.)

***Abstract*—The process of identifying optimal threshold for multi-level thresholding in image segmentation is a challenging process. An efficient optimization algorithm is required to find the optimal threshold and various nature inspired; evolutionary optimization algorithms are presented by the research community. However, to improve the performance in finding optimal threshold value and minimize the error, reduces the searching time a hybrid optimization algorithm is presented in this research work using salp swarm optimization and ant colony optimization algorithm. The ant colony optimization algorithm is used to enhance the exploration and exploitation characteristics of salp swarm optimization in finding optimal threshold for the given image. Experimentation using standard images validates the proposed model performance in comparison with traditional optimization algorithms like moth flame optimization, whale optimization algorithm, grey wolf optimization, artificial bee colony and bee foraging optimization algorithms. Proposed hybrid optimization outperformed in all parameters compared to traditional optimization algorithms and provides better optimal thresholds for the given input image.**

***Index Terms*—Multi-level thresholding, image segmentation, nature inspired optimization, ant colony optimization, salp swarm optimization algorithm, peak signal to noise ratio, structural similarity index, threshold**

I. Introduction

The demand for computer vision systems and the wide utilization of digital electronic devices with cameras requires special image treatment software for applications in medical diagnosis, surveillance, and industrial implementations, etc., The first step of this kind of systems need to segment the input image which requires thresholding. The attention towards obtaining better image thresholding is ever increasing over the decade. Thresholding is a form of segmentation which separates pixels into groups based on the intensity level considering threshold values. Thresholding is a complex process and depends on the segmentation requirements, the thresholding is categorized into two levels as bi-level thresholding and multi-level thresholding. In the bi-level thresholding, the high intensity pixel values are considered as objects and rest of the pixels are considered as background. Based on the threshold value, the pixels are selected, if the pixel is below the threshold, then it is selected as one category and if the threshold is low then it is selected as another category. The final output bi-level threshold will contain only two colors. Whereas in the multilevel thresholding, different region pixels are separated using different threshold values to represent the object in an image. So that the final image will be same as the original with improved features. Most of the real time applications requires this multi-level thresholding.

Generally, the thresholding problem is summarized based on the finding the best threshold value for the given image. The threshold points depend on the image histogram and each image has different threshold values. One of the best methods to select optimal threshold is Otsu's method and Kapur's method [1]. However, searching the optimal threshold for multi-level thresholding is a NP-hard problem and a challenging process. For minimum threshold requirements, the classical methods are well suited however the accuracy of the segmentation is greatly affected and it increases the computational cost and time when the number of thresholds increases. To overcome this optimization algorithms are incorporated in finding optimal threshold values. Various metaheuristic and evolutionary algorithms were presented to solve the complex problem. Algorithms like particle swarm optimization (PSO) [2], Moth flame optimization (MFO), and Whale optimization algorithm (WOA) [3] Grey wolf optimization (GWO) [4], artificial bee colony optimization algorithms (ABC) [5, 6] are used for identifying optimal solution in multi-level thresholding process. Each optimization algorithms have their own merits and demerits. For example, PSO global search ability is better and it requires minimum parameters. But PSO local search ability is very weak. In case of convergence, MFO is poor as it exhibits premature convergence. GWO and WOA effectively

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*Corresponding author

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avoids local optimal trap but their convergence speed is low and provides low accuracy and precision. In case of ABC the exploration ability is limited and faces issues while solving complex problems.

In order to improve the optimal thresholding search process, and to find the optimal solution for the multi-level thresholding problem a hybrid optimization algorithm is presented in this research work using salp swarm optimization and ant colony optimization algorithms. The feature merits of these optimization algorithms are incorporated to improve the performance of multilevel thresholding. The balance between exploration and exploitation characteristics of salp swarm optimization is further optimized using ant colony optimization in finding the optimal thresholding process. In the first step, the best solutions are obtained through salp swarm optimization and then ant colony optimization is used to update the optimal solution again to attain better performance. The objective of this research work is to improve the process of finding optimal thresholding and minimize the error. The contributions made in this research work are presented as follows.

- Presented a hybrid optimization algorithm for gray scale multilevel image segmentation using salp swarm optimization and ant colony optimization algorithms to find the optimal thresholding values for the given image.
- Presented a detailed experimentation using standard images and the performances are measured in terms of mean, standard deviation, peak signal to noise ratio and structural similarity index.
- Presented a detailed comparative analysis with existing optimization algorithms like moth flame optimization, grey wolf optimization, whale optimization algorithm, artificial bee colony and bee foraging algorithm to demonstrate the better performance of proposed model.

The remaining discussions are arranged as follows. A brief literature review is presented in Section II. The hybrid optimization algorithm mathematical model is presented in Section III and experimental results are presented in Section IV. The last part of discussion covers the conclusion and future scope of the research work.

II. Literature Review

This section presents a brief literature analysis on multi-level image thresholding approaches evolved in recent times. The methodologies are discussed and the performances are analyzed based on the results and the findings are summarized in the last as research findings. A novel two-dimensional histogram-based thresholding approach presented in [7] included gravitational search algorithm. The objective of the works is to enhance the segmentation efficiency by finding optimal thresholds. Thus, the presented exponential Kbest gravitational search algorithm combines the entropy function to refine the thresholding process and attained better segmentation performances compared to traditional approaches.

The multilevel thresholding process presented in [8] considered Otsu and Kapur methods for image segmentation. The presented approach combines the evolutionary differential search algorithm to find optimal threshold values for segmenting gray scale images. Quantitative and qualitative analysis confirms that the performance of the proposed model is better than the traditional search methods. A modified fuzzy entropy based multilevel thresholding approach presented in [9] incorporated levy flight firefly algorithm for color image segmentation. The presented approach considers equal entropies for all the region which minimizes the fitness function and provides better thresholding values. The adapted levy flight enhances the search space and provides optimal thresholds for better segmentation. Experimental results are compared with traditional Kapur's entropy and confirmed the presented approach better efficiency.

A variational model decomposition based multilevel thresholding approach was presented in [10] for computationally effective color image segmentation. The presented threshold selection procedure decomposes the histogram into multiple sub models and frames the minimized Otsu's objective function. Then based on the minimum point search and cross point search the thresholds are extracted effectively with minimum effort. Compared to traditional optimization algorithms, the performance of decomposition-based approach is computationally faster and provides better performances in image segmentation. The multilevel thresholding model presented in [11] incorporated dragon fly optimization to identify optimal thresholds for image segmentation. The swarming behavior of dragon flies are optimized through self-adaptive process which fine tunes the optimization model parameters. The self-adaptive scheme enhances the exploration and exploitation abilities of dragon fly algorithm and provides global optimal solution for thresholding. Similar dragon fly algorithm was presented in [12] for multilevel thresholding in medical image segmentation. The presented approach uses histograms to classify the image pixels and considers the pixel spatial information for medical image segmentation. The best threshold is obtained by the optimization algorithm which is better than the traditional methods.

The multilevel thresholding model reported in [13] included a heuristic thresholding which combines the whale optimization algorithm, particle swarm optimization and gray wolf optimization with thresholding and evaluated the performances. The presented approach identifies optimum thresholds and utilizes class variance criterion as fitness function to attain better performances than traditional algorithms. Reduced computation time is observed as the feature merits of the presented multilevel thresholding model. The multilevel image thresholding model presented in [14] considered many objective optimizations which has seven functions for image segmentation. The presented approach utilizes knee evolutionary algorithm to identify the Pareto optimal solution for seven objective functions.

The solutions obtained for the objective functions enhances the segmentation performances in terms of PSNR, SSIM and computational time compared to traditional methods. Similar Pareto optimal set was used in [15] to enhance the Kapur and Otsu objective functions and improve the segmentation performance of multilevel thresholding. The presented approach incorporates multiple Meta heuristic algorithms to optimize the objective function and reduces the computation cost better than the existing approaches.

The image thresholding model presented in [16] incorporated teaching learning-based optimization algorithm to obtain optimal threshold values for multilevel thresholding. The presented approach minimizes the cross entropy and identifies the optimal solution based on the mutual interaction concept in teaching learning optimization model. The performance of presented model is experimentally compared with honey bee mating optimization and quantum Particle Swarm Optimization in terms of PSNT and uniformity. An improved version of teaching learning-based optimization algorithm was presented in [17]. The presented approach initially determines the learner learning methods in teacher phase using random numbers. Further the global optimization ability of optimization algorithm is improved by random learning methods. Additionally, mutation crossover and self-feedback learning are incorporated to improve the exploration ability compared to other optimization algorithms.

An improved emperor penguin-based optimization model was presented in [18] for multi-level image thresholding. To minimize the computation complexity while calculating the number of thresholds. The presented approach identifies the optimal solution. In the process of finding the optimal solution, the search ability of optimization algorithm is improved thorough Gaussian mutation and levy flight. These methods provide better balance between the exploration and exploitation characteristics and obtained better segmentation accuracy compared to existing methods. An enhanced Harris Hawks optimization algorithm was presented in [19] for multilevel image segmentation. The presented swarm-based optimization model is formulated based on the hawks catching the rabbits. The limitation in trapping local optimal solution of Harris Hawks' optimization algorithm is improved by incorporating salp swarm optimization algorithm. So that better exploration and exploitation trends are obtained in the process of finding optimal solution. The presented approach initially generates a solution and divides them into two. Further exploratory and exploitative phases of Harris Hawks is applied to the first half and salp swarm is applied to the second half for solution update. Finally, the best solutions from both subsets are selected as optimal thresholds and it is used to segment the gray scale image.

In order to overcome the limitations in traditional methods in multilevel image thresholding, a genetic algorithm-based thresholding model presented in [20] reduced the computation complexity compared to existing methods. The presented hyper heuristic approach identifies the optimal execution sequence and obtains optimal thresholds using genetic algorithm. Experimentations on benchmark images demonstrates the better performance of proposed model in terms of accuracy compared to other optimization algorithms. An adaptive equilibrium optimization model was presented in [21] for multilevel thresholding, which presents a modified version of traditional equilibrium optimizer. The presented approach obtains adaptive decision for the search agents which enhances the overall performance compared to gray wolf optimization, whale optimization, wind driven optimization and squirrel search optimization algorithms. A hybrid optimization algorithm presented in [22] for multilevel image thresholding incorporated butterfly optimization algorithm and gases Brownian motion optimization for identifying optimal threshold vales. The presented approach initially creates a solution using image histogram considering the optimization algorithms and update the solution based on the exploration and exploitation characteristics. Performance analysis considering the metrics PSNR and SSIM and compared the hybrid model results with traditional optimization algorithms for better validation.

An improved artificial bee colony optimization model for multilevel thresholding presented in [23] reported an optimal solution by combining the thresholding problem in sine cosine algorithm. High threshold levels are obtained in the presented model with better peak signal to noise ratio (PSNR). An entropy based automatic image thresholding was presented in [24], which utilizes Shannon synergic entropy to attain reasonable threshold to gray scale images. Similarly a recursive minimum cross entropy model was presented in [25] for automatic image thresholding. However automatic image thresholding lags in performance when the input image has multiple features. An enhanced differential evolution based multilevel thresholding model presented in [26] utilized thresholding in medical image processing and attained better mean, signal to noise ratio values.

Based on the detailed literature study given above, it is identified that exploration and exploitation ability of traditional optimization algorithms are limited. An unbalanced exploitation and exploration features are observed in few optimization algorithms. This unbalance exploration and exploitation features are overcome by hybrid algorithm. The major issue in hybridizing optimization algorithm is selection of suitable optimization models. Incorporating one algorithm with other should be done based on the optimization characteristics without increasing the computation complexity. Thus, a hybrid optimization model is presented for multilevel thresholding in the following section.

III. Proposed Hybrid Optimization Algorithm

The proposed hybrid optimization for multilevel thresholding is presented in this section. The proposed model incorporates salp swarm optimization (SSO) and ant colony optimization (ACO) algorithms in which salp swarm has better exploration and exploitation abilities and avoids local optimal constraints. The predation behavior salp are used to solve complex optimization problem. However, to provide better balance between exploration and exploitation for salp, ant colony optimization algorithm is incorporated to find the optimal solution. Thus, the hybrid optimization algorithm performances increase in the multilevel image thresholding process. Generally thresholding is defined based on the histogram and the optimal thresholds are in the distinct valley of histogram. However, identifying this optimal threshold is quite complex and challenging as the histogram has wide peaks and valleys which are different from each other.

In the bi-level image thresholding process, optimal thresholds are used to separate image into two parts. Whereas when the thresholds increased, separating image into multiple parts is quite complex thus, multi-level thresholding is introduced for precise image separation. The major objective in multi-level image thresholding is to obtain optimal threshold value for image segmentation. Thus, for an image I which has m+1 classes are segmented with m optimal threshold values is mathematically formulated as follows.

$$\begin{cases} M_0 = \{g(x,y) \in I \mid 0 \le g(x,y) \le t_1 - 1\} \\ M_1 = \{g(x,y) \in I \mid t_1 \le g(x,y) \le t_2 - 1\} \\ \cdots \\ M_j = \{g(x,y) \in I \mid t_j \le g(x,y) \le t_{j+1} - 1\} \\ M_m = \{g(x,y) \in I \mid t_m \le g(x,y) \le L - 1\} \end{cases} \tag{1}$$

where the threshold values are represented as t for image I. The pixel gray level value is represented as $g(x, y)$ and the number for gray levels are represented as L. If the gray levels are considered as in the range of 0 to L–1, then the probability of gray level (P_i) is formulated as

$$P_i = h(i)/N, \text{ for } i = 0,1,2,\cdots,L-1 \tag{2}$$

where the number of pixels in gray level is represented as $h(i)$ and the total number of pixels in image is represented as N. In case if there are m thresholds such as t_1, t_2, ⋯ t_m and it segments the gray levels of image into m+1 classes, then the class mean values μ_m, total mean value μ_T and class occurrence probabilities ω_m are formulated as

$$\text{Class mean } \mu_m = \sum_{i=t_m}^{t_{m+1}-1} \frac{iP_i}{\omega_i} \tag{3}$$

$$\text{Class occurrence probability } \omega_m = \sum_{i=t_m}^{t_{m+1}-1} P_i \tag{4}$$

$$\text{Total mean value } \mu_T = \sum_{i=0}^{L-1} iP_i \tag{5}$$

Based on the class mean, class occurrence probability and total mean values, the objective function for multi-level thresholding is formulated as

$$f = \sum_{m=0}^{M} \omega_m (\mu_m - \mu_T)^2 \tag{6}$$

where ω_m indicates the class occurrence probabilities, μ_m indicates the class mean, μ_T indicates the total mean. The proposed hybrid optimization algorithm is used to optimize the objective function and to find the optimal solution for the multilevel thresholding. Fig. 1 depicts an overview of the proposed hybrid optimized multi-thresholding process.

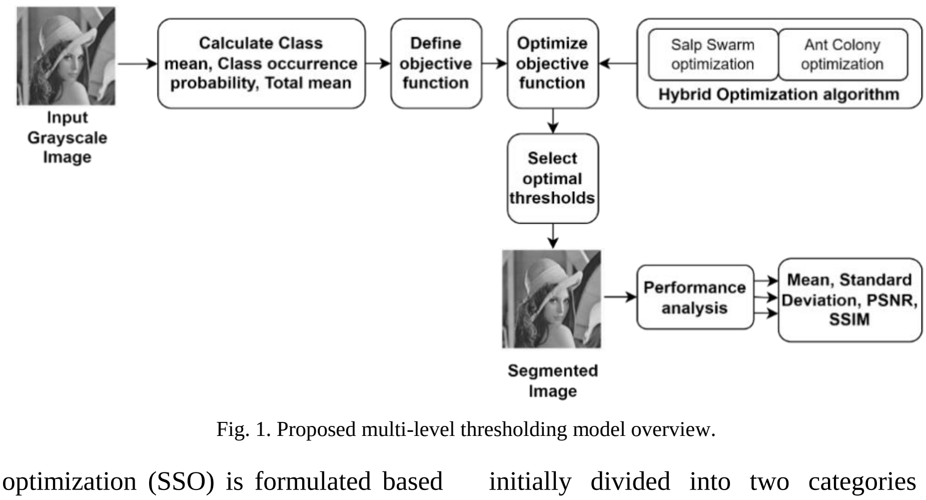

Fig. 1. Proposed multi-level thresholding model overview.

Salps swarm optimization (SSO) is formulated based on the salps which have transparent barrel shaped body and looks like a jelly fish. The movements of salps are similar to jelly fish where it uses water to pump into body and move forward. In deep oceans, a swarm shape is formed by the salps which is technically described as salp chain as illustrated in Fig. 2. This chain is formed for better locomotion and foraging and based on this the mathematical model of salp swarm optimization is formulated. The entire population in the salp chain is initially divided into two categories as leaders and followers. Generally the salp in the front is considered as leader and the remaining salps are considered as followers. The role of leader is to lead the swarm to search space and followers will follow the leader. The salps position in the search space are generally mentioned as a two dimensional matrix $\boldsymbol{x}$ and the food source is represented as f_d for the target group. The position update of salps are formulated as

$$x_j^n = \begin{cases} f_{d_j} + k_1\left(\left(\mathrm{ub}_j - \mathrm{lb}_j\right)k_2 + \mathrm{lb}_j\right) & k_3 \geq 0 \\ f_{d_j} - k_1\left(\left(\mathrm{ub}_j - \mathrm{lb}_j\right)k_2 + \mathrm{lb}_j\right) & k_3 < 0 \end{cases} \quad (7)$$

where the position of leader in jth dimension is represented as x_j^n and the food source position is represented as f_{d_j}. The lower and upper bound dimensions are represented as lb_j and ub_j respectively. The other parameters like k_2 and k_3 are coefficients which are generally random numbers in the range [0, 1].

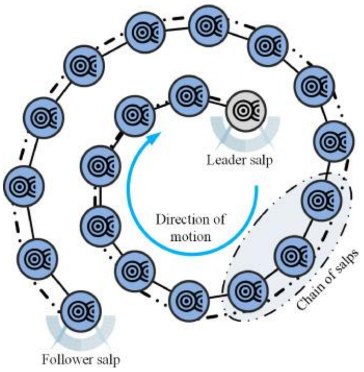

Fig. 2. Salp chain.

It can be observed from the equation that the leader has the option to update the position of food source with other members. The coefficient k_1 provides better exploration and exploitation balance in salp swarm optimization which is mathematically formulated as

$$k_1 = 2\exp\left[-\left(4L/N\right)^2\right] \quad (8)$$

where the maximum number of iterations is indicated as L and the current iteration is indicates as N. The position update of the followers is mathematically formulated as

$$x_j^i = \frac{1}{2}aT^2 + v_0 T \quad (9)$$

where v_0 is the initial speed, T indicates the time. The ratio of initial and final speed is indicated as

$$a = \frac{v_{\text{final}}}{v_0},\ v_{\text{final}} = \frac{x - x_0}{T}$$

Further to provide better balance between exploration and exploitation for salp, Ant Colony Optimization (ACO) algorithm is incorporated and find the optimal solution. ACO is formulated based on the ant food foraging behavior. The movement of ants, and their coordination in findings optimal food source is formulated to solve the real-life problems. Generally, the movements of ant are in random nature and it leaves pheromone trails on the path so that other ants will trace the pheromone and follow towards the food source. So, when each move towards a direction of other ants based on pheromone, it leaves again a pheromone trace so that other can able to follow easily. Thus, the path where a greater number of ants moved has higher pheromone density which leads other ants to move towards the food source and back to the colony. In the optimization problem the evaporation of pheromone avoids local optimal solution which is the merits of the ant colony optimization algorithm. The ant food searching features are used to optimize the salp swarm optimization algorithm to obtain better threshold values for the multilevel image segmentation. Fig. 3 depicts the simple illustration of ant colony optimization algorithm food foraging and optimal path finding process.

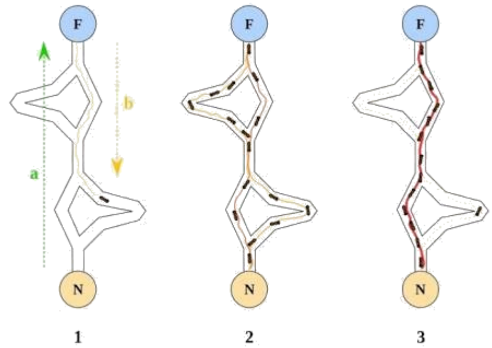

Fig. 3. Ant colony optimization.

For the mathematical model, n number of ants are considered and the movement of ants are initially considered as random in nature. The pheromone information is represented as α and the weighing factor for the heuristic information is represented as β. In the construction phase, each ant moves from one location to other location and it is formulated as a probabilistic transition process as follows.

$$p_{(l,m)(i,j)}^n = \frac{\left(\tau_{i,j}^{(n-1)}\right)^\alpha \left(\eta_{i,j}\right)^\beta}{\sum_{(i,j)\in\rho_{(l,m)}} \left(\tau_{i,j}^{(n-1)}\right)^\alpha \left(\eta_{i,j}\right)^\beta} \quad (10)$$

where the pheromone information level from one location to other location is represented as $\tau_{i,j}^{(n-1)}$, heuristic information is represented as $\eta_{i,j}$. The next location is represented as ρ and the constant parameter which describes the pheromone information and heuristic information is represented as α and β respectively. The heuristic information $\eta_{i,j}$ is formulated as

$$\eta_{i,j} = \frac{1}{z} v_c\left(i,j\right) \quad (11)$$

where variation in the image pixel intensity value is represented as v_c.

In the update stage, two operations are performed in the ant colony optimization in order to update the pheromone matrix. Based on the movement of ants, the matrix is updated and based on the movement of all the ants the matrix is updated again to obtain optimal solution. The update of pheromone matrix based on the ant movement is formulated as

$$\tau_{i,j}\left(n-1\right) = \begin{cases} \left(1-\vartheta\right)\tau_{i,j}\left(n-1\right) + \vartheta\Delta\tau_{i,j}\left(k\right), & \text{if } \left(i,j\right) \text{ is visited by the ant} \\ \tau_{i,j}\left(n-1\right), & \text{otherwise} \end{cases} \quad (12)$$

where ϑ indicates the evaporation rate. The matrix update based on the movement of all the ants is formulated as

$$\tau_n = (1-\varphi)\tau_{n-1} + \varphi\tau_n \tag{13}$$

where the decay coefficient of pheromone is represented as φ. The termination criteria of the proposed approach using parameter settings like the number of iterations and number of ants the process can be terminated. The optimization algorithm provides better solutions so that better balance between exploration and exploitation characteristics is obtained in the salp swarm optimization in the process of identifying optimal threshold for image segmentation.

Further the computation complexity of hybrid optimization algorithm which combines salp swarm optimization (SSO) and Ant colony optimization (ACO) is given as Salp swarm ant colony optimization (SSACO) as follows:

$$O(\text{SSACO}) = \alpha O(\text{SSO}) + O(\text{ACO}) \tag{14}$$

where

$$O(\text{SSO}) = O\left[t_{\max}\left(K \cdot N + \text{EF} \cdot N + N \log N\right)\right] \tag{15}$$

$$O(\text{ACO}) = O\left(\text{NC} \cdot n^2 \cdot m\right) \tag{16}$$

where fitness evaluation is indicated as EF, population size is indicated as N, K indicates the problem dimension, number of individuals updated is indicated as α. NC indicates the number of cycles; m indicates the number of ants.

The steps followed in the hybrid optimization algorithm is presented in Algorithm 1:

Algorithm 1: Initialize salp population, ant population

Begin
Obtain fitness value for each salp
Update position of leader salp considering upper and lower bounds as per equation (7)
Update position of follower salp as per equation (9)
Define coefficient k as per equation (8)
Initialize ants,
Update movement of ants as per equation (10) as probabilistic transition process
Update heuristic information as per equation (11)
Update pheromone matrix as per equation (12)
Define final ant movement of ant in optimal path as per equation (13)
Obtain computation complexity for proposed model using equation (14)
end
end

IV. Results and Discussion

The performance of the proposed hybrid optimization for multi-level image thresholding is verified through simulation analysis performed in MATLAB R2019 installed in an Intel i5 processor with 32 GB memory. The operating system of computer is Windows 11 and the benchmark images are used for experimental analysis. Total 6 images are taken from USC-SIPI for analysis which are ‘Lena’, ‘Baboon’, ‘Plane’, ‘Bridge’, ‘Peppers’, and ‘Male’ images. The size of the images is 512×512 and samples used in the experimentation are depicted in Fig. 4 respectively for Lena, baboon, plane, bridge, male and peppers. The statistical performance analysis considers the results of 100 individual experimental observations for the proposed hybrid optimization algorithm and finds the best optimal number of thresholds for input images. Standard parameters like mean, standard deviation, peak signal to noise ratio and structural similarity index are considered for analysis. The mathematical formulations for Peak Signal to Noise Ratio (PSNR), Root Mean Squared Error (RMSE), and Structural Similarity Index (SSIM) are given as follows:

$$\text{PSNR} = 20\log_{10}\left(\frac{255}{\text{RMSE}}\right) \tag{17}$$

$$\text{RMSE} = \sqrt{\frac{\sum_{i=1}^{x}\sum_{j=1}^{y}\left[I(i,j) - \tilde{I}(i,j)\right]^2}{xy}} \tag{18}$$

$$\text{SSIM} = \frac{\left(2\mu_I\mu_{\tilde{I}} + c_1\right)\left(2\sigma_{I,\tilde{I}} + c_2\right)}{\left(\mu_I^2 + \mu_{\tilde{I}}^2 + c_1\right)\left(\sigma_I^2 + \sigma_{\tilde{I}}^2 + c_2\right)} \tag{19}$$

where the error between segmented image and original image is measured in terms of RMSE, the size of the image is represented as $x \cdot y$. The mean intensity of segmented and original image is represented as $\mu_{\tilde{I}}$ and μ_I respectively. Similarly, the standard deviation of segmented and original image is represented as $\sigma_{\tilde{I}}$ and σ_I respectively. When the mean square is near to zero if will affect the stability thus two constants are used such as c_1 and c_2. These two constants are used to improve the stability.

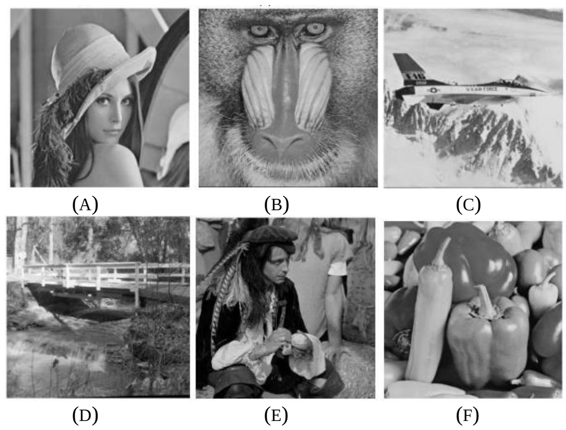

Fig. 4. Input Images: (A) Lena, (B) Baboon, (C) Plane,(D) Bridge, (E) Male, and (F) Peppers.

For the given input the parameters like mean, standard deviation are measured and listed in Table I and Table II respectively. To validate the better performance of proposed hybrid optimization model SS-ACO, traditional optimization algorithms like Moth Flame Optimization

(MFO), Whale Optimization Algorithm (WOA), Grey Wolf Optimization (GWO), Artificial Bee Colony (ABC) and Bee Foraging algorithm (BFA) are comparatively analyzed. The results of existing methods are obtained from Zhang *et al*.'s research work [27]. Additionally conventional ACO and SSO models are executed separately and their results are included in the comparative analysis. Different levels of thresholds are used to measure the performance like 2, 3, 4 and 5 and the maximum iterations are fixed for the threshold are 25, 40, 50 and 100 respectively. From the comparative analysis it is identified that the proposed model performance is better than the traditional algorithms.

TABLE I: MEAN VALUES OBTAINED BY THE TRADITIONAL AND PROPOSED OPTIMIZATION ALGORITHMS

Images	Threshold	MFO	WOA	GWO	ABC	BFA	ACO	SSO	SS-ACO
Lena	2	1961.7	1961.8	1961.6	1961.7	1961.8	1961.8	1961.9	**1964.8**
	3	2128.2	2128.2	2127.5	2128.0	2128.3	2128.5	2128.7	**2130.5**
	4	2191.8	2189.9	2190.9	2190.6	2191.9	2194.7	2194.9	**2200.1**
	5	2217.1	2215	2216.3	2217.5	2217.7	2217.8	2217.9	**2218.6**
Baboon	2	1549.1	1548.9	1548.9	1549.1	1549.1	1549.6	1549.8	**1552.4**
	3	1639.3	1638.1	1638.8	1639.2	1639.5	1639.6	1639.9	**1642.7**
	4	1692.8	1689.8	1692.5	1692.7	1693.2	1693.4	1693.4	**1695.3**
	5	1718.6	1717.8	1718.5	1718.8	1719.0	1721.2	1721.5	**1722.6**
Plane	2	1948.7	1948.7	1948.6	1948.7	1948.7	1948.9	1948.9	**1949.6**
	3	2024.7	2024.8	2024.5	2024.5	2024.8	2024.9	2025.0	**2025.4**
	4	2069.7	2069.6	2069.0	2069.5	2070.1	2070.5	2070.9	**2071.7**
	5	2095.9	2093.8	2095.2	2095.9	2096.1	2097.2	2098.0	**2098.1**
Bridge	2	2532.5	2532.1	2532.3	2532.5	2532.5	2532.9	2532.9	**2534.7**
	3	2722.2	2721.7	2722	2721.9	2722.3	2724.2	2724.4	**2736.4**
	4	2822.2	2819.4	2821.9	2821.9	2822.4	2823.7	2823.7	**2825.4**
	5	2873.6	2871.2	2873.4	2873.9	2874.1	2875.5	2876.4	**2879.6**
Male	2	2997.6	2997.7	2997.6	2997.6	2997.7	2998.4	2998.6	**2999.4**
	3	3180.4	3180.3	3179.9	3179.9	3180.5	3181.6	3181.5	**3182.6**
	4	3265.7	3265.9	3265.8	3265.4	3265.9	3265.9	3266.0	**3267.5**
	5	3312.3	3312.3	3312.3	3312.3	3312.6	3313.5	3313.9	**3315.6**
Peppers	2	2532.3	2532.3	2532.2	2532.4	2532.3	2533.6	2534.0	**2534.5**
	3	2703.4	2703.2	2702.8	2703.4	2703.6	2704.4	2705.7	**2711.4**
	4	2765.6	2765.9	2765.7	2765.5	2766.4	2767.2	2767.3	**2768.3**
	5	2810.6	2810.2	2809.8	2810.5	2810.8	2813.1	2813.4	**2814.6**

TABLE II: STANDARD DEVIATION VALUES OBTAINED BY THE TRADITIONAL AND PROPOSED OPTIMIZATION ALGORITHMS

Images	Threshold	MFO	WOA	GWO	ABC	BFA	ACO	SSO	SS-ACO
Lena	2	1.10E-01	9.60E-02	4.40E-01	3.00E-01	7.50E-03	7.52E-03	7.53E-03	**7.60E-03**
	3	2.10E-01	7.10E-01	1.50E-01	4.10E-01	9.20E-03	9.22E-03	9.24E-03	**9.28E-03**
	4	2.30E-01	1.10E+01	2.00E-01	3.10E-01	7.10E-03	7.11E-03	7.11E-03	**7.12E-03**
	5	7.30E-01	7.30E-01	3.00E-01	3.10E-01	2.70E-01	2.71E-01	2.71E-01	**2.72E-01**
Baboon	2	6.10E-02	6.80E-01	4.20E-01	3.00E-02	2.80E-02	2.82E-02	2.84E-02	**2.89E-02**
	3	3.70E-01	1.00E+01	1.50E+00	5.00E-01	1.60E-02	1.64E-02	1.66E-02	**1.72E-02**
	4	1.50E+00	1.10E+01	1.20E+00	4.70E-01	3.60E-02	3.63E-02	3.65E-02	**3.69E-02**
	5	6.60E-01	5.20E+00	1.00E+00	2.30E-01	4.90E-02	4.94E-02	4.96E-02	**4.98E-02**
Plane	2	7.70E-02	2.10E-02	1.60E-01	1.10E-01	1.20E-02	1.24E-02	1.26E-02	**1.28E-02**
	3	3.20E-01	1.20E-01	7.00E-01	5.20E-01	1.80E-02	1.86E-02	1.86E-02	**1.91E-02**
	4	7.00E-01	1.50E-01	1.80E-01	7.30E-01	1.80E-02	1.88E-02	1.89E-02	**1.91E-02**
	5	4.00E-01	6.60E-01	1.70E-01	2.00E-01	2.10E-02	2.11E-02	2.12E-02	**2.13E-02**
Bridge	2	6.00E-02	1.20E+00	5.40E-01	6.00E-02	4.10E-12	4.11E-12	4.11E-12	**4.12E-12**
	3	4.10E-01	1.70E+00	1.50E+00	7.10E-01	6.50E-02	6.56E-02	6.59E-02	**6.61E-02**
	4	1.20E+00	9.40E+00	2.10E+00	9.50E-01	2.60E-01	2.62E-01	2.64E-01	**2.68E-01**
	5	1.10E+00	6.00E+00	1.90E+00	4.00E-01	2.40E-01	2.44E-01	2.46E-01	**2.52E-01**
Male	2	5.30E-02	4.80E-02	2.80E-01	3.30E-01	1.70E-02	1.72E-02	1.74E-02	**1.78E-02**
	3	3.80E-01	4.40E-01	2.30E+00	7.80E-01	3.30E-03	3.34E-03	3.36E-03	**3.42E-03**
	4	6.90E-01	1.40E-01	2.50E+00	5.40E-01	2.20E-02	2.24E-02	2.26E-02	**2.28E-02**
	5	7.30E-01	1.40E+00	1.00E+00	3.40E-01	2.70E-02	2.76E-02	2.79E-02	**2.84E-02**
Peppers	2	5.50E-02	2.60E-01	4.00E-01	5.70E-02	1.90E-02	1.94E-02	1.98E-02	**2.00E-02**
	3	5.50E-01	2.40E+00	2.70E+00	3.40E-01	7.40E-03	7.42E-03	7.48E-03	**7.52E-03**
	4	1.40E+00	1.30E+00	1.40E+00	1.00E+00	2.30E-01	2.32E-01	2.34E-01	**2.34E-01**
	5	4.40E-01	4.40E+00	2.20E+00	3.50E-01	9.80E-03	9.82E-03	9.86E-03	**9.90E-03**

Further to performance of proposed model and existing optimization models are graphically represented for the objective function values for different number of thresholds for each input image. Fig. 5 depicts the convergence curves for the objective function values obtained by the proposed and traditional optimization algorithm for Lena Image with number of thresholds 2, 3, 4 and 5 respectively. It can be observed from the results, the performance of the proposed model is maximum for all the threshold values which due to the optimization of fitness function in the hybrid optimization process. This improvement and better performance of the proposed model is observed for thresholds 4 and 5 and it is clearly depicted in Fig. 5(c) and Fig. 5(d) respectively.

Fig. 6 depicts the convergence curves for the objective function values obtained by the proposed and traditional optimization algorithm for Baboon Image with number of thresholds 2, 3, 4 and 5 respectively. When the number of thresholds is 2, the maximum iteration is 25 and the proposed model has reached maximum of 1552.36, whereas existing models ABC attained 1549.07, MFO attained 1549.06, GWO attained 1548.91, WOA attained 1548.94, and BFA attained 1549.08, ACO attained 1549.64, SSO attained 1549.82, which is lesser than the proposed model. Similarly, when the number of thresholds is 3, for maximum iteration of 40, the proposed model attained 1643, whereas ABC attained 1639.17, MFO attained 1639.31, GWO attained 1638.8, WOA attained 1638.09, BFA attained 1639.53, ACO attained 1639.64, SSO attained 1639.88, which is lesser than the proposed model.

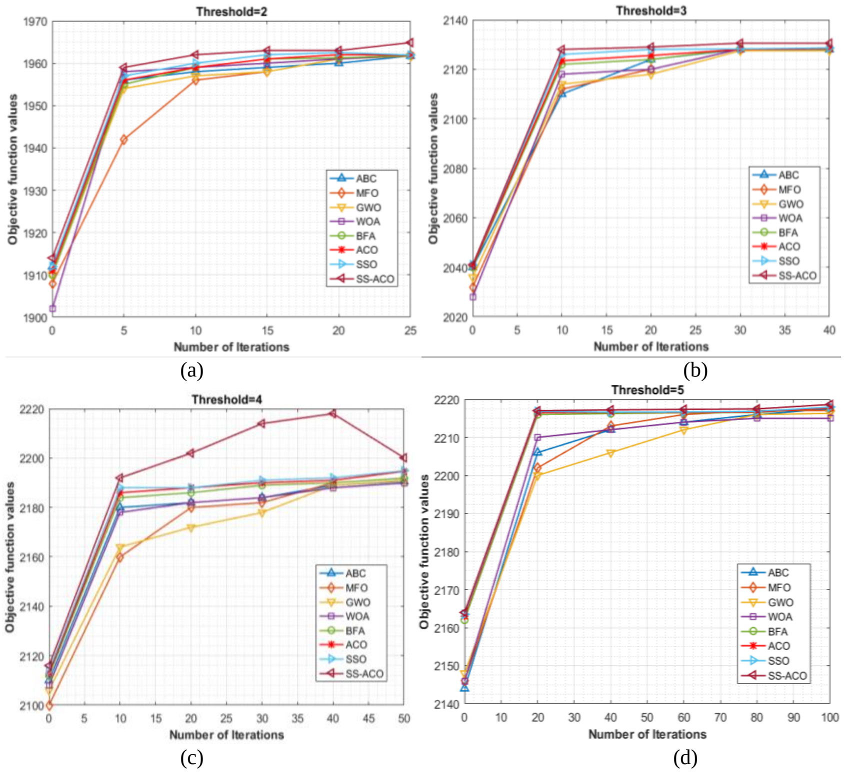

Fig. 5. Objective function values for Lena Image (a) Threshold = 2, (b) Threshold = 3, (c) Threshold = 4, and (d) Threshold = 5.

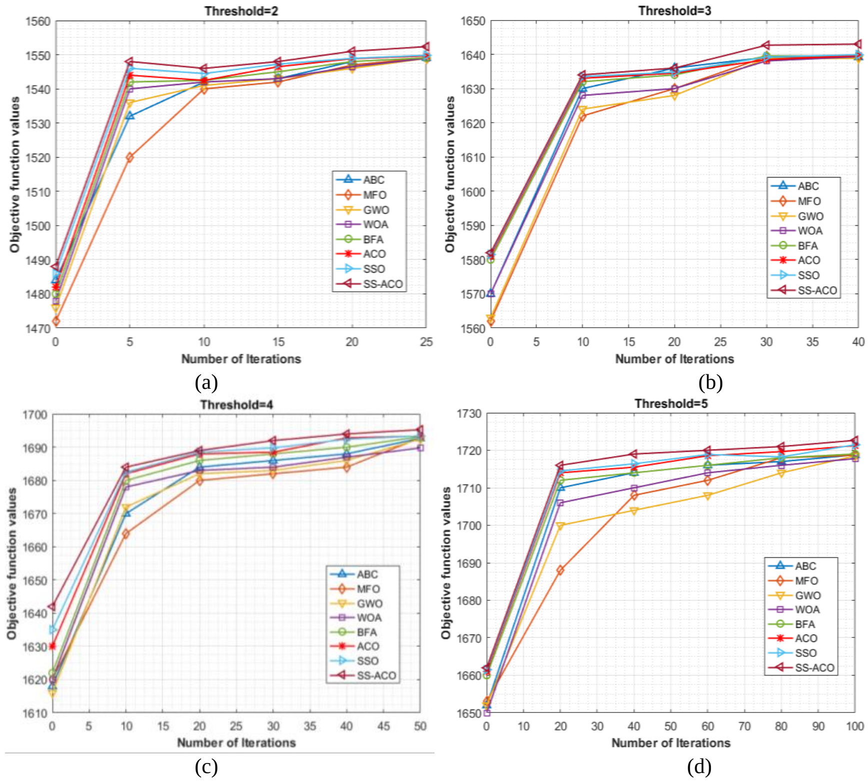

Fig. 6. Objective function values for Baboon image: (a) Threshold = 2, (b) Threshold = 3, (c) Threshold = 4, and (d) Threshold = 5.

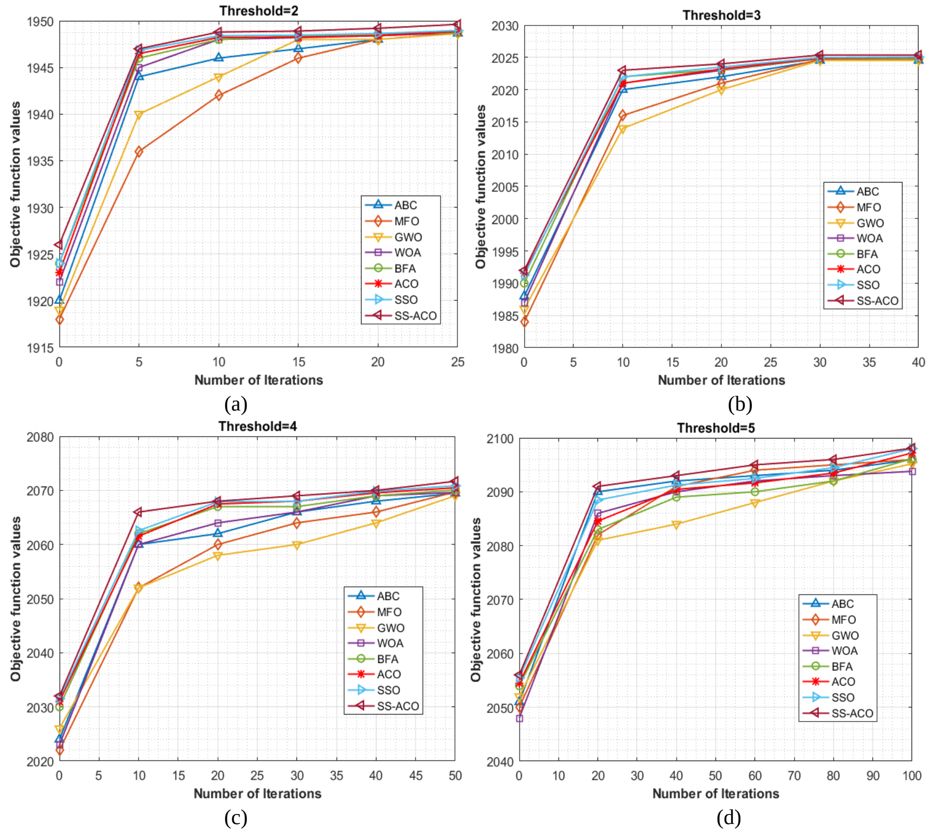

Fig. 7. Objective function values for Plane image: (a) Threshold = 2, (b) Threshold = 3, (c) Threshold = 4, and (d) Threshold = 5.

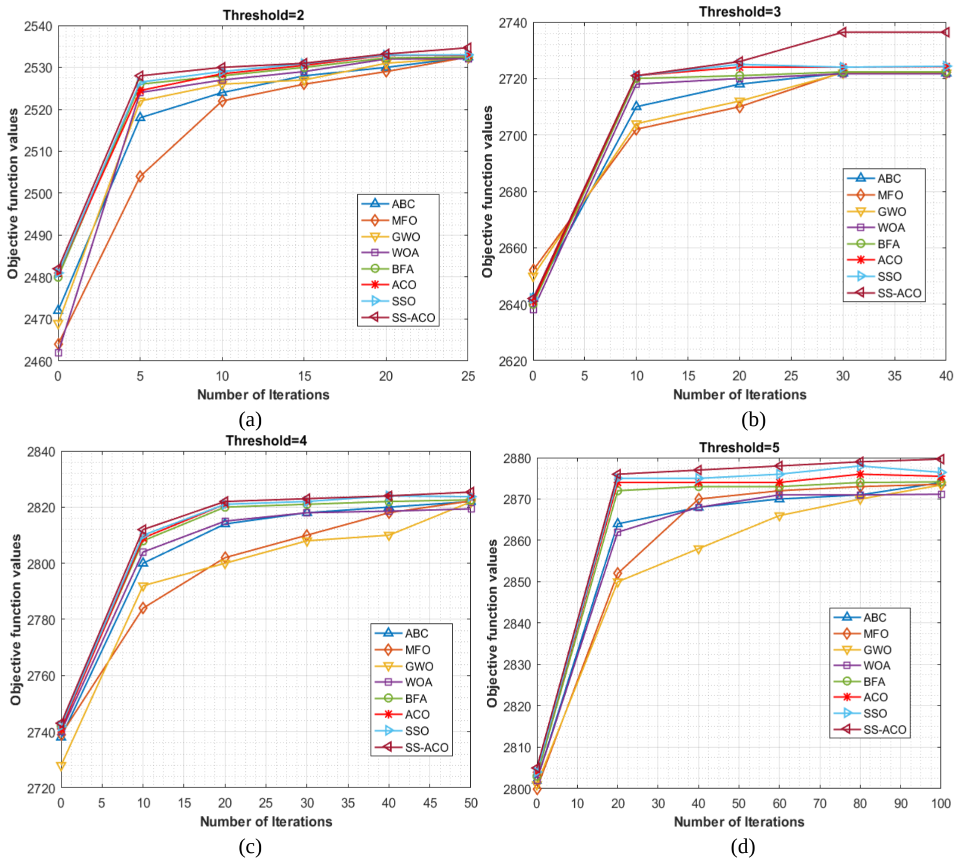

Fig. 8. Objective function values for Bridge image; (a) Threshold = 2, (b) Threshold = 3, (c) Threshold = 4, and (d) Threshold = 5.

Fig. 7 depicts the convergence curves for the objective function values obtained by the proposed and traditional optimization algorithm for plane image with number of thresholds 2, 3, 4 and 5 respectively. When the number of thresholds is 2, the maximum iteration is 25 and the proposed model has reached maximum of 1949.62, whereas existing models ABC attained 1948.66, MFO attained 1948.7, GWO attained 1948.63, WOA attained 1948.72, BFA attained 1948.72, ACO attained 1948.86, and SSO attained 1948.96, which is lesser than the proposed model. Similarly, when the number of thresholds is 3, for maximum iteration of 40, the proposed model attained 2025.36, whereas ABC attained 2024.52, MFO attained 2024.67, GWO attained 2024.53, WOA attained 2024.8, BFA attained 2024.82, ACO attained 2024.99, and SSO attained 2025.05, which is lesser than the proposed model.

Fig. 8 depicts the convergence curves for the objective function values obtained by the proposed and traditional optimization algorithm for bridge image with number of thresholds 2, 3, 4 and 5 respectively. When the number of thresholds is 2, the maximum iteration is 25 and the proposed model has reached maximum of 2534.68, whereas existing models attained in the range of 2532 which is lesser than the proposed model. Similarly, when the number of thresholds is 3, for maximum iteration of 40, the proposed model attained 2736.41, whereas existing models attained in the range of 2721 which is lesser than the proposed model.

Fig. 9 depicts the convergence curves for the objective function values obtained by the proposed and traditional optimization algorithm for male image with number of thresholds 2, 3, 4 and 5 respectively. When the number of thresholds is 2, the maximum iteration is 25 and the proposed model has reached maximum of 2999.41, whereas existing models attained in the range of 2997 which is lesser than the proposed model. Similarly, when the number of thresholds is 3, for maximum iteration of 40, the proposed model attained 3182.65, whereas existing models attained in the range of 3180 which is lesser than the proposed model.

Fig. 10 depicts the convergence curves for the objective function values obtained by the proposed and traditional optimization algorithm for peppers image with number of thresholds 2, 3, 4 and 5 respectively. When the number of thresholds is 2, the maximum iteration is 25 and the proposed model has reached maximum of 2534.48, whereas existing models attained in the range of 2532 which is lesser than the proposed model. Similarly, when the number of thresholds is 3, for maximum iteration of 40, the proposed model attained 2711.45, whereas existing models attained in the range of 2703 which is lesser than the proposed model.

Table III depicts the PSNR values obtained by the proposed model and existing optimization algorithms for different input images and different number of thresholds. Results confirmed that the proposed hybrid optimization exhibits better performances than the existing optimization algorithms for PSNR metric.

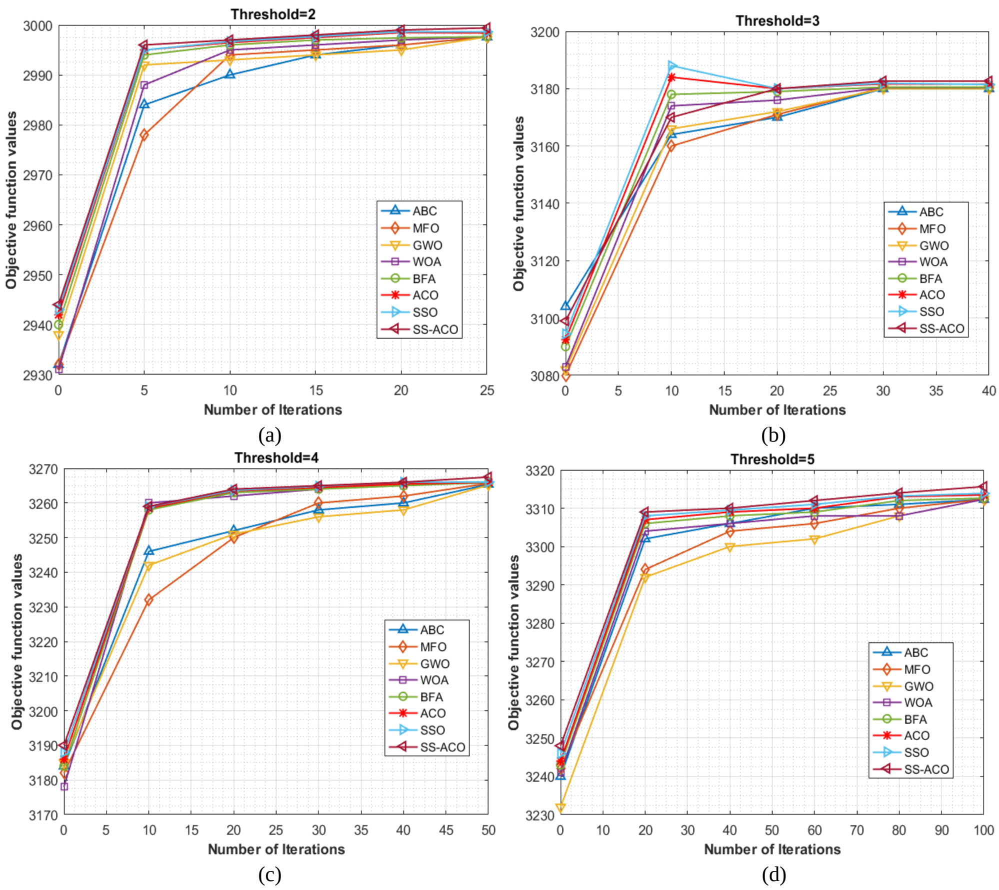

Fig. 9. Objective function values for Male image: (a) Threshold = 2, (b) Threshold = 3, (c) Threshold = 4, and (d) Threshold = 5.

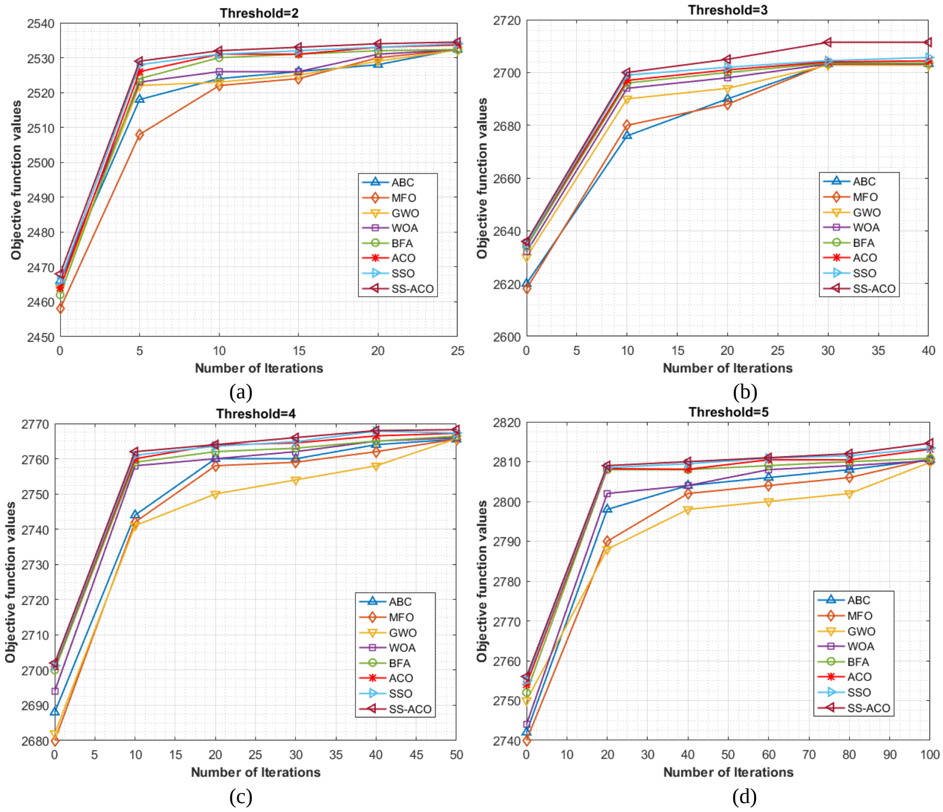

Fig. 10. Objective function values for Peppers image: (a) Threshold = 2, (b) Threshold = 3, (c) Threshold = 4, and (d) Threshold = 5.

TABLE III: PEAK SIGNAL TO NOISE RATIO (PSNR) VALUES OBTAINED FOR THE EXISTING AND PROPOSED OPTIMIZATION ALGORITHMS

Images	Threshold	MFO	WOA	GWO	ABC	BFA	ACO	SSO	SS-ACO
Lena	2	20.4031	20.399	20.3969	20.3791	20.4085	20.6021	20.8046	21.2656
	3	23.7615	23.7649	23.7296	23.7475	23.7666	23.8248	23.8848	24.2655
	4	25.3341	25.3163	25.3282	25.3245	25.339	25.4864	25.5684	25.8984
	5	26.089	26.0791	26.1133	26.1386	26.1552	26.2145	26.4748	26.8946
Baboon	2	20.1223	20.1119	20.1151	20.1202	20.1185	20.2348	20.4865	21.0456
	3	21.6483	21.6537	21.6524	21.6434	21.6722	21.7448	21.8426	22.6548
	4	23.0435	22.9932	23.0368	23.0513	23.0542	23.1415	23.2894	23.6985
	5	24.1957	24.2428	24.2239	24.2292	24.2828	24.3565	24.4849	24.6689
Plane	2	22.3125	22.3292	22.2938	22.2995	22.3375	22.4848	22.6418	23.4586
	3	22.9564	22.9556	22.9144	22.971	23.0121	23.2214	23.4642	24.2656
	4	24.1453	24.2009	24.1069	24.1483	24.2147	24.2322	24.2446	24.6598
	5	25.3359	25.2805	25.3294	25.3174	25.3863	25.4441	25.6443	26.3565
Bridge	2	20.2589	20.2582	20.2629	20.2639	20.2645	20.3265	20.4848	20.8978
	3	22.8918	22.8892	22.5503	22.8919	22.8968	22.9194	22.9294	23.1465
	4	25.1462	25.1146	25.1253	25.1489	25.1553	25.2624	25.4842	26.5124
	5	26.7464	26.6925	26.7398	26.7636	26.7669	26.8241	26.8648	27.1264
Male	2	18.8528	18.8687	18.8493	18.8459	18.8603	18.8842	18.9241	19.6845
	3	21.3091	21.3039	21.2939	21.3297	21.3338	21.3546	21.4248	22.3145
	4	24.9122	24.9486	24.9308	24.9487	24.9546	24.9648	24.9742	25.6455
	5	26.7943	26.8167	26.7865	26.7973	26.8232	26.8648	26.8947	27.0489
Peppers	2	20.1167	20.1196	20.0962	20.1035	20.1189	20.6542	20.7845	21.4654
	3	22.6075	22.6047	22.5901	22.6052	22.6169	22.6848	22.8814	23.6548
	4	23.6414	23.6509	23.6447	23.6554	23.6643	23.6823	23.6455	24.4897
	5	25.1473	25.1477	25.1385	25.1498	25.1659	25.1894	25.2644	26.5648

TABLE IV: SSIM VALUES OBTAINED FOR THE EXISTING AND PROPOSED OPTIMIZATION ALGORITHMS

Images	Threshold	MFO	WOA	GWO	ABC	BFA	ACO	SSO	SS-ACO
Lena	2	2.45E-01	2.45E-01	2.45E-01	2.45E-01	2.45E-01	2.42E-01	2.40E-01	2.35E-01
	3	3.14E-01	3.14E-01	3.14E-01	3.14E-01	3.14E-01	3.12E-01	3.10E-01	3.04E-01
	4	3.75E-01	3.73E-01	3.75E-01	3.73E-01	3.75E-01	3.70E-01	3.68E-01	3.63E-01
	5	4.24E-01	4.27E-01	4.27E-01	4.30E-01	4.32E-01	4.30E-01	4.28E-01	4.20E-01
Baboon	2	5.72E-01	5.72E-01	5.72E-01	5.72E-01	5.72E-01	5.68E-01	5.66E-01	5.62E-01
	3	6.70E-01	6.69E-01	6.70E-01	6.69E-01	6.71E-01	6.70E-01	6.66E-01	6.59E-01
	4	7.28E-01	7.25E-01	7.28E-01	7.28E-01	7.28E-01	7.24E-01	7.22E-01	7.18E-01
	5	7.80E-01	7.80E-01	7.81E-01	7.81E-01	7.83E-01	7.80E-01	7.83E-01	7.85E-01
Plane	2	2.82E-01	2.82E-01	2.81E-01	2.82E-01	2.82E-01	2.84E-01	2.85E-01	2.86E-01

	3	3.44E-01	3.44E-01	3.43E-01	3.44E-01	3.44E-01	3.45E-01	3.48E-01	3.65E-01
	4	4.04E-01	4.05E-01	4.04E-01	4.04E-01	4.05E-01	4.10E-01	4.11E-01	4.15E-01
	5	4.35E-01	4.34E-01	4.34E-01	4.34E-01	4.36E-01	4.38E-01	4.37E-01	4.39E-01
Bridge	2	4.84E-01	4.84E-01	4.84E-01	4.84E-01	4.84E-01	4.88E-01	4.89E-01	4.94E-01
	3	6.07E-01	6.06E-01	6.06E-01	6.07E-01	6.07E-01	6.09E-01	6.10E-01	6.17E-01
	4	6.94E-01	6.92E-01	6.93E-01	6.94E-01	6.94E-01	6.95E-01	6.96E-01	6.99E-01
	5	7.52E-01	7.50E-01	7.51E-01	7.53E-01	7.53E-01	7.54E-01	7.58E-01	7.63E-01
Male	2	3.81E-01	3.81E-01	3.81E-01	3.81E-01	3.81E-01	3.80E-01	3.82E-01	3.82E-01
	3	4.94E-01	4.94E-01	4.93E-01	4.94E-01	4.95E-01	4.91E-01	4.94E-01	4.86E-01
	4	5.61E-01	5.64E-01	5.63E-01	5.64E-01	5.64E-01	5.63E-01	5.66E-01	5.67E-01
	5	6.26E-01	6.27E-01	6.25E-01	6.26E-01	6.27E-01	6.28E-01	6.29E-01	6.34E-01
Peppers	2	2.22E-01	2.22E-01	2.22E-01	2.22E-01	2.22E-01	2.24E-01	2.26E-01	2.29E-01
	3	3.04E-01	3.04E-01	3.04E-01	3.04E-01	3.04E-01	3.06E-01	3.07E-01	3.08E-01
	4	3.64E-01	3.65E-01	3.65E-01	3.66E-01	3.68E-01	3.69E-01	3.67E-01	3.68E-01
	5	4.24E-01	4.23E-01	4.24E-01	4.24E-01	4.25E-01	4.24E-01	4.25E-01	4.29E-01

Table IV depicts the SSIM values obtained by the proposed model and existing optimization algorithms for different input images and different number of thresholds. Results confirmed that the proposed hybrid optimization exhibits better performances than the existing optimization algorithms for both PSNR and SSIM metric. This indicates that the proposed hybrid optimization algorithm based multi-level thresholding improves the image segmentation details and provides better features than the traditional algorithms.

From the experimental analysis it can be observed that the performance of the proposed hybrid optimization algorithms is much better than other optimization algorithms. In case of mean, the proposed model attained higher mean value for all the images compared to other optimization algorithms. Similarly, the proposed model attained better standard deviation values for all the images. In case of PSNR and SSIM proposed hybrid optimization algorithm exhibited its better performances for all the images.

V. Conclusion

A hybrid optimization algorithm for multi-level thresholding is presented in this research work using salp swarm optimization and ant colony optimization algorithm. The ant colony optimization algorithm in the proposed work is used to optimize the parameters of salp swarm optimization to attained improved performance and minimum error in the image thresholding process. Experimentations on standard images validates the proposed model better performance in terms of mean, standard deviation, peak signal to noise ration and structural similarity index. For comparative analysis, traditional optimization algorithms like moth flame optimization, whale optimization algorithm, grey wolf optimization, artificial bee colony and bee foraging algorithm are used. Experimental results provide the better performance of proposed model over existing optimization algorithms. In future the research work can be extended by increasing the number of thresholds to obtain more details from the input image through the hybrid optimization algorithm.

Conflict of Interest

The authors declare no conflict of interest.

Author Contributions

K. Manikandan is the primary researcher of the work and main author of the paper. B. Sudhakar have contributed expertise in image processing. He also acted in supervisory role. All authors had approved the final version.

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B. Sudhakar presently working as assistant professor in Annamalai University Chidambaram, India. He has more than 16 years of teaching experience in the Department of Electronics and Communication Engineering. He has published several papers in reputed international journals. His research interest is in the areas of wireless communication, speech processing and image processing.

K. Manikandan presently working as assistant professor in the Government College of Engineering, Thanjavur, Tamil Nadu, India, He has more than 10 years of teaching experience in the Department of Electronics and Communication Engineering. He is currently pursuing a Ph.D. degree from Annamalai University, Tamil Nadu, India.