Boosting Marine Predators Algorithm by Salp Swarm Algorithm for Multilevel Thresholding Image Segmentation

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Abstract

Pixel rating is considered one of the commonly used critical factors in digital image processing that depends on intensity. It is used to determine the optimal image segmentation threshold. In recent years, the optimum threshold has been selected with great interest due to its many applications. Several methods have been used to find the optimum threshold, including the Otsu and Kapur methods. These methods are appropriate and easy to implement to define a single or bi-level threshold. However, when they are extended to multiple levels, they will cause some problems, such as long time-consuming, the high computational cost, and the needed improvement in their accuracy. To avoid these problems and determine the optimal multilevel image segmentation threshold, we proposed a hybrid Marine Predators Algorithm (MPA) with Salp Swarm Algorithm (SSA) to determine the optimal multilevel threshold image segmentation MPASSA. The obtained solutions of the proposed method are represented using the image histogram. Several standard evaluation measures, such as (the fitness function, time consumer, Peak Signal-to-Noise Ratio, Structural Similarity Index, etc.) are employed to evaluate the proposed segmentation method’s effectiveness. Several benchmark images are used to validate the proposed algorithm’s performance (MPASSA). The results showed that the proposed MPASSA got better results than other well-known optimization algorithms published in the literature.

Keywords Image segmentation · Multilevel thresholding · Meta-heuristic algorithms · Marine Predator algorithm · Salp Swarm algorithm
1 Introduction

Image segmentation is an important and challenging process [31]. It is involved in various fields, including pattern recognition, digital image processing, and artificial intelligence [32]. It is considered one of the most critical image processing steps that separate the image components into different parts by merging the same pixel groups. It is also used in the process of extracting object-related features from an image [37]. This is not an easy task; usually, the images contain some unwanted background noise. Various techniques are used in the segmentation process to subtract objects from images and separate or split them from backgrounds [21]. Image segmentation is also an essential step in computer vision. Also, it represents a necessary technique in image analysis, especially for medical image analysis. The images are divided into two types: color and gray ideas. Each of them has different methods of segmentation [46].

Image segmentation methods are classified into layer-based segmentation methods and block-based segmentation methods, as given in Fig. 1. Among the most popular segmentation techniques used are Threshold, Histogram, Edge detection, Watershed Transformation, Clustering, and Region-based methods. As for separating the objects from the background, the Threshold method is used. The segmentation method, which uses threshold, is characterized by its simplicity and accuracy compared to other methods [23]. So, it has received the attention of many researchers in this field.

The threshold method is widely used for dividing pixels in an image into different classes [49, 50]. There are two methods to determine image thresholds: the first is bi-level thresholding, and the second is multilevel thresholding. The first method divides the image into two categories based on the threshold value. It groups pixels densest from a threshold value into one class and pixels less dense than a threshold value into another level. They are often used to separate the foreground and background of the images. The process of dividing into two categories is insufficient, especially when the image is more complex and contains several objects with similar gray levels [45].

Therefore, it is necessary to extend the threshold levels from bi-level to multilevel [44]. The multilevel threshold (MTH) splits an image into several classes belonging to multiple objects.
in the image. In this method, it is possible to reveal more information and more items from the segmented image. Additionally, several histogram methods have been developed, such as Otsu’s method and Kapoor’s method. The basis for their work is to maximize the variance between classes and entropy to achieve homogeneity between categories. One of the problems caused by these methods is the complexity of the mathematical operations, primarily as the number of threshold levels increases to obtain better threshold values. Therefore, this problem’s solution lies in combining these Metaheuristic algorithms. Several algorithms are used by researchers, such as particle swarm optimization, social-spider optimization [40], and others [13]. In this case, conflict problems arise to achieve a specific objective; this target may not be suitable for image types. This is because each goal has a particular kind of image that makes it powerful.

In the Otsu-based method, the best value of the threshold is maximizing the variance between classes. So, the choice of optimal thresholds in multilevel was a challenge over decades. Which affects segmentation accuracy. To address this weakness, this paper proposes an efficient multilevel threshold method depending on an enhanced Marine Predators Algorithm for image segmentation. The Salp Swarm Algorithm is used as a local search to improve the basic MPA’s performance in this proposed method. The proposed algorithm, MPASSA, is a hybrid optimization algorithm for MTH that beats on the shortcomings of individual optimization algorithms using the force of both MPA and SSA. The candidate solutions for the proposed method are represented using an image histogram. The hybrid technique combines the characteristics of two different methods (MPA and SSA). Therefore, the proposed hybrid algorithm (MPASSA) averts getting stuck on a local optimum and has a high ability to find the optimal solution for the image. Several standard evaluation metrics, such as the function of fitness, signal-to-noise ratio, structural similarity index, consumer time, etc., are used to evaluate the proposed segmentation method’s effectiveness. The MPASSA is assessed by using two experiments that have a set of images. In the first experiment set, two gray images are used. These images were widely applied in different studies to assess various segmentation algorithms. At the second experiment set, three-color images are used. Also, these images were involved in other studies to evaluate various segmentation algorithms. The results of MPASSA are compared with several optimization algorithms, such as WOA, PSO, AOA, SSA, MPA, and it shows significant performance improvement. The proposed method MPASSA has proved its effectiveness in all test cases. Both experiment sets’ performance indicates that the MPASSA is an effective segmentation method, and it can be used in various segmentation applications. The results reveal that the proposed MPASSA is better than other known optimization algorithms published in the literature.

The main contributions of this study are summarized as follows.

1) This research proposes a new image segmentation method using a multilevel threshold based on using optimization method.
2) The SSA operators are used to enhance the exploitation ability of the MPA, called MPASSA.
3) This research tests the proposed method’s performance in two experiment sets using two popular grayscale images and three-color popular images.
4) The proposed method is compared with several state-of-the-art methods.

The design of this paper is given as follows. Section 2 contains a literature review of the past and current image segmentation by multilevel thresholding algorithms. Section 3 presents the research methodology and techniques used in Image segmentation by multilevel thresholding
algorithms. Section 4 illustrates the implemented proposed algorithms, the evolution measurements that have been used to test and evaluate the proposed algorithms, and research discussion and results. Finally, Section 5 presents the conclusion of this research, followed by suggestions and motivations for future work in the field of Hybrid Algorithms.

2 Background

One of the most critical image analysis problems and processing is the pixel segment into its various categories. The goal of segmentation is to identify elements and isolate them from the background and distinguish between pixels to improve contrast [41]. Several common methods can be used to solve this problem [5, 8, 12, 20, 26, 43, 53]. The most common segmentation techniques that researchers still use nowadays are Threshold, Histogram, Edge detection, Watershed Transformation, clustering, and Region-based methods [1].

There are two types of thresholds; threshold one value is called bi-level thresholds. If more than one threshold value is used, it is called a multilevel point, the second type. In the first type, pixels are divided into two categories. Pixels with an intensity level higher than the threshold value are classified as objects, while the remaining pixels are classified as a part of the background [38]. However, the second one used a multilevel threshold to divide the grayscale images into sections where it became necessary to extend the bi-level threshold levels to the multilevel. When the image is more complex and contains several objects with similar gray levels, it is also used with pictures with colored backgrounds. The multilevel threshold mechanism, which has more than one threshold, divides the image into several classes belonging to multiple objects. Therefore, it results in multiple items with one background. In this way, more information and things can be revealed from the segmented image [2].

Among the most critical methods used with threshold segmentation are the Otsu and Kapur methods [30]. The Otsu method increases the contrast between image classes. In contrast, the Kapur method maximizes entropy as a measure of homogeneity between categories. Both approaches have proven to be one of the most widely used forms of image processing. They are also considered accurate and effective alternatives to pixilation in the bi-level threshold technique. It can be used in a multilevel threshold, but its accuracy decreases as the thresholds’ number increases, leading to increased complexity. Many other approaches adopt entropy, such as Tallies entropy, Fuzzy entropy, the Shannon entropy, and Renyi’s entropy. The same problem of increasing computational complexity appears at a multilevel threshold [38]. Therefore, to solve such issues, Meta-Heuristic algorithms provide highly accurate results in most cases. The Meta-Heuristic algorithms are essential tools for solving optimization problems’ intricacies with high accuracy [4].

According to the official data provided by those countries, a new forecasting method is proposed in [19] to forecast the number of people infected with Covid-19 in some countries. The proposal offers an improvement to the ANFIS model to predict the number of injured people, depending on another optimizer, the Marine Predator algorithm. The algorithm is used to improve ANFIS parameters, as well as enhance prediction performance. The results of the prediction performance evaluation of the proposed method MPA-ANFIS were compared with several other ways. The result was that the proposed approach significantly outperforms almost all techniques and measures of performance. Among the performance measures that were
compared are, mean absolute error (MAE), Root Mean Squared Relative Error (RMSRE), Mean Absolute Percentage Error (MAPE), and others \[9, 14\].

In [25], a new variant of MPA is proposed. The proposed method’s performance is tested on several problems, including the real-world engineering design and CEC-2017 tests. The algorithm was compared to other optimization algorithms: the first is GA and PSO, which is one of the algorithms that have been well studied, the second is GSA, CS, and SSA, as the algorithms developed in the recent period, third is CMA-ES, SHADE, and LSHADE-cnEpSin, are the algorithms that are as optimizers for performance. They are also IEEE CEC competition winners. The results were that the Marine Predator algorithm ranked second as the best performing method, and it showed competitive results compared to LSHADE-cnEpSin. The Marine Predator algorithm is one of the winning algorithms in the CEC 2017 competition. The statistical analysis presented in that paper shown that the Marine Predator algorithm can work as a high-performance optimizer. It also proved that the Marine Predator algorithm is significantly superior to the SSA, GSA, CMA-ES, PSO, CS, and GA algorithms. The study also showed the similarity of performance statistically for each Marine Predator, SHADE, and LSHADE-cnEpSin.

In [34], a novel hybrid algorithm is presented. The Proposed method ensembles Salp Swarm and Multi-objective Salp Swarm in solving the optimization problems for both single and multiple objectives. The Salp’s primary behavior is a crowd of strains while on the move to search for food [6]. The researcher tested both algorithms on several mathematical optimization tasks to observe, monitor, and confirm their behavior in finding the best solution. The results showed that the Salp swarm algorithm could optimize the initial random solutions and are close to being the optimum. The results also showed that the multi-objective Salp Swarm algorithm could converge Pareto optimal solutions. The study also showed that both proposed algorithms could solve complex and computationally costly engineering design problems (such as designing marine propellers). The research also indicates that the proposed algorithms have many advantages that distinguish them in solving many real-world situations.

In [3], an effective multilevel threshold (MTH) method is proposed for image segmentation, including medical image segmentation including COVID-19 CT images. Suggested is the Marine Predatory Animal (MPA) algorithm. MPA is a new SI method. According to the researchers’ study, the proposal provides the first application for use in image segmentation. The (MFO) algorithm was used in the MPA optimization process. The new proposal has been called MPAMFO. The request was evaluated with various images, as it included cross-sectional images of Coronavirus (COVID-19). The results showed stable and good performance in all tests. Also, several comparisons were applied to prove the MPAMFO proposal’s superiority over many algorithms, including PSO, GWO, and CS, in terms of SSIM, fitness value, and PSNR. The proposed algorithm has proven to be highly effective. Therefore, it is possible to improve it and apply it in various improvement processes, including data clustering, machine job scheduling, time series prediction, cloud computing, etc.

A new proposal combining the SSA algorithm with the PSO algorithm is given in [28]. This proposal is to enhance SSA’s ability for exploration and exploitation by using PSO characteristics to improve the quality of the SSA for searching for results. Thus, the rate of convergence increases. The proposed algorithm was evaluated with two experiments; first, it was tested on 15 standard groups. The second was applied to determine the optimal subset of the features from among ten UCI groups to increase classification accuracy. The results from the two experiments were compared to several algorithms, including SSA. The work SSA with the PSO algorithm gives better results in performance measures, including chosen feature ratio,
processing unit time, accuracy, and evaluating the fitness function. This means that hybridization of the SSA gives better results than it does separately.

In [47], a novel objective function and a new application of the MPA approach are presented to properly extract the nine parameters of the PV module’s TDPV model. This study aims to obtain an accurate PV model for any commercial PV panel, which plays an essential role in the grid-connected PV power systems’ simulation studies. In this study, the optimization problem’s main objective is to minimize a function representing the current error. The MPA technology was successfully utilized to reduce the objective function, obtaining the PV module’s TDPV model’s nine parameters. Various comparisons were exhibited to check the efficacy of the offered TDPV model using the MPA technology. The proposed algorithm was successfully employed to optimally design the parameters of two marketable KC200GT and MSX-60 PV modules. The optimal parameters, realized using the MPA-TDPV model, are coherent with those achieved using other algorithms. The MPA approach has recorded lower optimal fitness values of $1.245e-14$ and $7.458e-13$ for KC200GT and MSX-60 PV modules. Furthermore, the simulation outcomes of the MPA-TDPV model concur with the measured data for these well-known PV panels under several environmental situations. The MPA-TDPV model’s ACE indicates a lower value than other PV models for the marketable PV panels. This points out the proposed approach’s superiority, efficacy, and robustness for achieving a precise TDPV model-based PV panel. With the help of the MPA approach, accurate modeling of any marketable PV panel can be realized. Moreover, the MPA technology can be further extended to solve various optimization problems in power system applications, energy storage devices, and smart grids.

In [52], an innovative objective function with a robust and reliable optimization algorithm named the marine predators’ algorithm (MPA) is proposed to provide the optimal pattern structure for three dimensions of PV arrays nine $\times$ 9, 16 $\times$ 16, and 25 $\times$ 25. The MPA is tested with several shade patterns and compared with manta ray foraging optimization (MRFO), Harris hawk optimizer (HHO), and particle swarm optimizer (PSO), as well as the total-cross, tied (TCT) connection. Several quality and statistical measures are computed, such as mismatch power loss, fill factor, percentage power loss, and Wilcoxon signed-rank test to assess the performance of the proposed approach. The research showed that the I-V and P-V characteristics were used to investigate the proposed MPA’s applicability compared with the other counterparts. Moreover, the mean execution time has been evaluated. The results reveal that MPA enhanced the PV array power by the percentage of 28.6%, 2.7%, and 5.7% in cases of 9 $\times$ 9, 16 $\times$ 16, and 25 $\times$ 25 PV arrays, respectively, and a uni-peak PV characterizes is achieved as well with lowest execution time and highest consistency in the results across the number of independent runs. Therefore, the authors recommend MPA as an efficient and applicable algorithm for PV reconfiguration systems at any dimension of PV array structures.

In [29], a node localization algorithm has been proposed based on Salp Swarm Algorithm (SSA), which handled the node localization problem as an optimization problem. The proposed algorithm has been implemented and validated in various WSN deployments using other target nodes and anchor nodes. Moreover, the proposed algorithm has been evaluated compared to four well-known optimization algorithms, namely PSO, BOA, FA, and GWO, in terms of localization accuracy, computing time, and several localized nodes. The obtained simulation results have proved the proposed algorithm’s superiority compared to the other localization algorithms regarding the various performance metrics. The proposed approach can be hybridized with different algorithms to reduce the localization error in future work.
In [27], an improved version of the salp swarm algorithm is introduced for predicting chemical compound activities. A set of assessment indicators are used to evaluate and compared with different algorithms, including particle swarm optimization (PSO), Grasshopper Optimization Algorithm (GOA), Grey Wolf Optimizer (GWO), Sine Cosine Algorithm (SCA), Whale Optimization Algorithm (WOA) using three initialization method, and a superior accuracy was obtained with our proposed approach. Also, compared with other algorithms that used the same data, this research’s system has a higher performance using fewer features. The previous algorithms (GOA, GWO, PSO, SSA, SCA, and WOA) are compared. Three different methods were used to initialize the various optimization algorithms to ensure the other optimizers’ capability to converge from various initial positions, namely mixed initialization, short initialization, and extensive initialization.

In [10], a new hybrid Arithmetic Optimization Algorithm (AOA) and Deferential Evolution (DE) algorithm (DAOA) is proposed for multi-thresholding image segmentation. The proposed algorithm employs the AOA algorithm to optimize the threshold and then uses this thresholding value to partition the images through DE. So, the DAOA integrates AOA global optimization and DE fast convergence. The experiment results were compared against four algorithms. The DAOA achieved better results than other methods; also, the DAOA provided a faster convergence with relatively lower CPU time. In the future, the DAOA can be applied to other complex image segmentation problems.

We concluded that the given methods in the literature are employed to solve the image segmentation problems by finding the optimal number of threshold values. However, finding these values is a complicated problem and needs an efficient method to determine them [48, 17]. Several optimization techniques proved their ability to solve this proposed and demonstrated that an efficient method is required. Thus, we proposed an effective method to address this problem and finding the optimal threshold values.

3 The research methodology

Before presenting the proposed hybrid algorithm (MPASS), we need to define the problem and understand the mathematical model for the main algorithms: Marine Predators Algorithm and Salp Swarm Algorithm. In this section, we present the formulation of the problem, MPA and SSA, and their main items.

3.1 Formulation of the problem

In this section, the problem formulation of multilevel thresholding is illustrated, which gives a mathematical definition through considering a gray level image $I$. The image $I$ is tested to be segmented consisting $K + 1$ classes. Each segmentation process requires division pixels of the image $I$ into subregions or classes as in Eq. (1). This can be done by determining $K$ thresholds \{$t_1, t_2, \ldots, t_K$\} [22].

$$G_0 = \{0 \leq I_{ij} \leq t_1 - 1\} = \{t_1 \leq I_{ij} \leq t_2 - 1\} = \{t_k \leq I_{ij} \leq L - 1\}$$

(1)
In given Equations, \( G_K \) represents \( K-th \) class of image \( I \), \( I(i, j) \) is the value of gray level to the pixel \((i, j)\), \( t_k \) where \((k = 1, \ldots, K)\) that define \( k-th \) threshold value, and \( L \) represents the gray levels of \( I \), all levels within the range \((0, 1, \ldots, L - 1)\).

Multilevel thresholding aimed to locate the optimal threshold values that divide \( I \) into several groups; Optimization methods can determine these values. One of the standard methods and well-known optimization function is Otsu’s method \([39]\). It is used in bi-level segmentation problems as well as in multilevel. In multilevel thresholding, Otsu’s technique locates the optimum threshold values of \( I \) by maximizing as in Eq. (2). It can be defined as the following:

\[
t_1^*, t_2^*, \ldots, t_k^* = F(t_1, t_2, \ldots, t_k)
\]

where \( F(t_1, \ldots, t_K) \) is the intra class difference (Otsu’s function) that defined in Eq. (3).

\[
F = \sum_{i=0}^{k} A_i (\eta_i - \eta_j)^2
\]

\[
A_i = \sum_{j=t_i}^{t_{i+1}-1} P_j
\]

\[
\eta_i = \sum_{j=t_i}^{t_{i+1}-1} \frac{P_j}{A_j}, \text{where } P_j = h(i)/N
\]

where \( \eta_i \) pointed to mean in tensity of image \( I \), with \( t_0 = 0 \) and \( t_{K+1} = L \). \( h(i) \) is frequency and \( P_j \) is probability of the \( i-th \) gray level. \( N \) is the all pixels in the evaluated \( I \).

### 3.2 Marine Predators Algorithm (MPA)

This part will explain the Marine Predators Optimization Algorithm (MPA) development process as an efficient and straightforward meta-heuristic optimization method \([19]\). The basis of the algorithm’s work is population. The first solution is distributed randomly on the search area in a uniform manner, as in Eq. (6):

\[
X_0 = X_{min} + \text{rand} \ (X_{max} - X_{min})
\]

where \( X_{min} \) and \( X_{max} \) are the minimum and maximum bound for variables, the rand is a random vector within range \((0, 1)\).

Based on the theory of survival of the fittest, an array can be constructed to include the best solution for the best predator. The best predator is the one that has the most talent for foraging. This matrix is called the elite. The array is represented mathematically as in Eq. (7).

\[
\text{Elite} = \begin{bmatrix}
X_{1,1}^1 & X_{1,2}^1 & \cdots & X_{1,d}^1 \\
X_{2,1}^1 & X_{2,2}^1 & \cdots & X_{2,d}^1 \\
\vdots & \vdots & \ddots & \vdots \\
X_{n,1}^l & X_{n,2}^l & \cdots & X_{n,d}^l
\end{bmatrix}
\]
As for the prey, it is arranged as in the elite matrix. As the predator sites update depending on this matrix. This means preparing the primary prey on which the (fittest) predator depends in the elite ranking. The prey matrix in Eq. (8).

\[
\text{Prey} = \begin{bmatrix}
X_{1,1} & X_{1,2} & \cdots & X_{1,d} \\
X_{2,1} & X_{2,2} & \cdots & X_{2,d} \\
\vdots & \vdots & \ddots & \vdots \\
X_{n,1} & X_{n,2} & \cdots & X_{n,d}
\end{bmatrix}
\]  

(8)

In Eq. (8), the \(X_{i,j}\) represents the \(j\)th dimension of \((i)\)th prey. It is noted that the optimization process is entirely linked directly and mainly to these two matrices.

The process of optimizing the algorithm and moving it from one phase to another depends heavily on the predator’s speed relative to the prey. Therefore, the process of improving the Marine Predators algorithm can be divided into three primary stages, depending on the different speed ratios for both the prey and the predator and the life of each of them. The steps are as follows: 1- The movement of the prey relative to the predator is faster with a high rate. 2- The movement of both predator and prey at equal or close speed. 3- The movement of the predator to the prey is faster, with a low rate.

**Phase No. 1** The exploration stage is where the prey moves at high speed to discover new search areas. At this stage, the predator should remain and monitor the prey’s movements. This stage’s performance is in the first third of the total iterations of development (i.e., \(1/3 \times \text{Max}_\text{iter}\)) as in Eq. (9).

\[
\text{stepsizes}_i \rightarrow = R \rightarrow B \otimes (\text{Elitel} \rightarrow_i - R \rightarrow B \otimes \text{Prey} \rightarrow_i)
\]

Where, \(i = 1 \ldots n\)

\[
\text{Prey}_i \rightarrow = \text{Prey}_i \rightarrow + P \cdot \text{CF} \rightarrow \otimes \text{stepsizes}_i \rightarrow
\]

\[
\text{CF} = (1 - \frac{\text{Iter}}{\text{Max}_\text{iter}})^{2\left(\frac{\text{Iter}}{\text{Max}_\text{iter}}\right)}
\]

Where CF is an adaptive variable for controlling the step volume of a predator. \(R_B\) represents random numbers and is represented by a vector. These numbers are regular in \([0,1]\) and represent Brownian motion. \(P = 0.5\) represents a vector and constant number for random numbers. The variable \(\text{Iter}\) represents the current iteration, while \(\text{Max}_\text{iter}\) represents the maximum iteration.

**Phase No. 2** At this point, both the predator and the prey are moving at the same speed. This part occurs in the middle stage of improvement in Eq. (10). Depending on the rule, the unit
pace ratio ($v \approx 1$), if prey moves in Lévy, the best-organized predator is Brownian motion. This can be considered a transitional stage between exploration and exploitation. Both exploitation and exploration are essential in this section.

**While** $1/3 \text{ Max}_\text{Iter} < \text{Iter} < 2/3 \text{ Max}_\text{Iter}$

$$\text{steps}ize_i \rightarrow = R \rightarrow L \otimes (\text{Elitel} \rightarrow i - R \rightarrow L \otimes \text{Prey} \rightarrow i)$$

$$\text{Prey}_i \rightarrow = \text{Prey}_i \rightarrow +P \cdot \text{CF} \otimes \text{steps}ize_i \rightarrow$$

Where $R_L$ refers to the random numbers, where these numbers are following the Lévy movement in distribution, the first half represents exploitation (represented by predators), Eq. (11) is applied to it. While the prey that represents the second half of the population assumes:

$$\text{steps}ize_i \rightarrow = R \rightarrow B \otimes (R \rightarrow B \otimes \text{Elitel} \rightarrow i - \text{Prey} \rightarrow i)$$

$$\text{Prey}_i \rightarrow = \text{Elitel}_i \rightarrow +P \cdot \text{CF} \otimes \text{steps}ize_i \rightarrow$$

$\text{Max}_\text{iter}$ is the overall number of generations. The $R_B$ and Elite simulate the predator’s movement in a Brownian motion, while the prey changes its position depending on the predator movement in Brownian fashion.

**Phase No. 3** This phase is the last of the optimization process. They represented when the predator’s movement is faster than a prey. The predator exploits the prey that is detected and attack it very quickly to get it. So, the exploitability is often high. The best motion for the predator in a low pace ratio ($v = 0.1$) is Lévy. This phase is executed on the last third of the iteration numbers ($\text{Iter} > 2/3 \text{ Max}_\text{iter}$), the predator follows Lévy. The predator will update its position in Eq. (12).

$$\text{steps}ize_i \rightarrow = R \rightarrow L \otimes (R \rightarrow L \otimes \text{Elitel} \rightarrow i - \text{Prey} \rightarrow i)$$

where,

$$\text{Prey}_i \rightarrow = \text{Elitel}_i \rightarrow +P \cdot \text{CF} \otimes \text{steps}ize_i \rightarrow$$

Step size is added to the Elite site for the predator’s movement to update the prey site. The doubling of the $R_L$ and Elite also simulates the predator’s movement within Lévy’s strategy.

### 3.2.1 Eddy formation and FADs’ Effect

Another point that causes a behavioral change in marine predators is environmental issues such as the eddy formation or Fish Aggregating Devices (FADs) effects. As mentioned in [28], Sharks spend over 80% of their time in the vicinity of FADs. The others are taking the long
jumps in different dimensions to find other prey. The effects of FADs can be mathematically expressed in Eq. (14).

\[
\begin{align*}
\text{prey}_i & = \left\{ \begin{array}{ll}
\text{prey}_i + CF \left[ \text{prey}_i \rightarrow \mathbb{X} \text{min} + r_i \right] \otimes U & \text{if } r \leq \text{FADs} \\
\text{prey}_i + [\text{FADs}(1 - r) + r] & \text{prey}_{r_1} - \text{prey}_{r_2} & \text{if } r > \text{FADs}
\end{array} \right.
\end{align*}
\]

Where FADs = 0.2 represent the probability of affected FADs on the process of the optimization. \( U \) is a vector of binary with matrices that have contained zero and one. This is done by generating an arbitrary vector in \([0,1]\) and update the array to zero if it’s less than 0.2, and one if it’s more. \( r \) is the uniform arbitrary number \([0,1]\). Both \((\mathbb{X}_{\text{min}}, \mathbb{X}_{\text{max}})\) are the vectors consist of (lower, upper) bounds of the dimensions. \( r_1 \) and \( r_2 \) represent indexes of random prey.

3.2.2 Marine memory

Figure 2 illustrates the second phase of optimization, in which the predator adopts the Brownian strategy better in searching for its prey within the field, as indicated in blue.

When optimization is in its final phase, algorithms need a high ability for exploitation. The third phase represents the last phase of optimization when the predator changes its behavior from Brown’s strategy to Levi so that the search process will be more efficient in a particular area. At the same time, the Convergence Factor (CF) has an excellent role for predators. This limits the search in several parts of the specific area for exploitation. It also avoids the effort in the search that extends from long steps as a result of using Levi’s strategy for non-promising areas in the field. The flowchart of the MPA algorithm is represented as shown in Algorithm 1.
3.3 Salp Swarm Algorithm (SSA)

The Salp algorithm is one of the meta-heuristic algorithms that has been successfully used in solving many optimization problems in various fields [34]. Mathematically, as we know, that the swarm is divided into a leader and followers. The leader guides his followers in their movements. The $X$ represents a swarm of $n$ of the Salps as Eq. (15), represented by a two-dimensional matrix. The fitness of each Salp is calculated to determine the best among them (meaning, defines the leader for the swarm). The leader positions will be updated by using Eq. (16).

$$
X_i = \begin{bmatrix}
X^1_1 & X^1_2 & \cdots & X^1_d \\
X^2_1 & X^2_2 & \cdots & X^2_d \\
\vdots & \vdots & \ddots & \vdots \\
X^n_1 & X^n_2 & \cdots & X^n_d
\end{bmatrix}
$$

(15)

$$
X^1_i = \{ y_i + ((u b_i - l b_i) r_2 + l b_i) r_3 \} r_4
$$

(16)

Where $x_i$ represents the position for the leader (first) Salp in the dimension $i$th, and $y_i$ is the food site in the $i$th dimension. $l b_i$ and $u b_i$ is the lower and upper bound at the $i$th dimension, respectively, and the coefficient $r_1$ is calculated by Eq. (17). $r_2$ and $r_3$ are random numbers between [0,1].
\[ r_1 = e^{-\left(\frac{t}{t}\right)^2} \]  

(17)

Where \( L \) is the upper iterations and \( l \) is the running iteration. Note that the coefficient \( r_1 \) is very significant in SSA because the balances of exploration and exploitation depend on it during the entire search process. As for the followers, Eq. (18) shows the updated positions.

\[ x'_i = \frac{1}{2} \lambda t^2 + \delta_0 t \]  

(18)

Where \( j \geq 2 \). \( x_i \) pointed to the site of the \( n \)th Salp in the \( i \)th dimension, \( \delta_0 \) represents an initial speed, \( t \) is the time, and \( \delta_0 = \frac{\delta_0}{\lambda t^2} \). The time in optimization points to the iteration. So, the difference between iterations is equal to 1. Considering the proposition that \( \delta_0 = 0 \), the following equation (in Eq. (19)) is employed for this issue.

\[ x'_i = \frac{1}{2} (x'_i + x'^{-1}_i) \]  

(19)

Where \( j \geq 2 \). In some cases, the Salp leaving outside of the search space, how we can bring them back to the search space in Eq. (20).

\[ x'_i = \left\{ \begin{array}{ll} \lambda_1 & \text{if} x'_i \leq \lambda_i \text{ or } x'^{-1}_i \leq \lambda_i \text{ or } x'^{-1}_i \leq \lambda_i \\ \end{array} \right. \]  

(20)

Exploration and exploitation, diversification and intensification, global search and local searches, few pairs of words are common in optimization algorithms. At least the optimization algorithms include one of those pairs. Here we will talk about exploration and exploitation. Exploration aims to discover new areas in the search area. This makes the search process not stop within one level, leading to discovering the optimal solution level. The exploitation aims to reach a better solution within the suitable and discovered solutions. A coefficient responsible for the balance between exploration and exploitation, it is called the coefficient \( c_1 \). It is calculated from the equation Eq. (2). The Pseudo-code of the SSA is given in Algorithm 2.

**Algorithm 2. The procedure of the Salp Swarm Algorithm**

- **Initialize** the salp population \( x_i \) \((i=1, 2, \ldots, n)\) considering \( \text{ub} \) and \( \text{lb} \)
- **While** (end condition is not satisfied) do
  - **Calculate** the fitness of each search agent (salp)
  - \( F = \text{the best search agent} \)
  - **Update** \( c_1 \)
  - **For** each salp in \( x_i \) do
    - **if** \((i = 1)\) then
      - **Update** the position of the leading Salp
    - **Else**
      - **Update** the position of the follower salp
  - **End if**
- **End while**
- **Return** \( F \)
1.1 The proposed hybrid algorithm (MPASSA)

The research introduces a hybrid algorithm used to segment images. The proposed hybrid algorithm determines the optimal multilevel threshold values that maximize Otsu’s objective function. The proposed algorithm is called MPASSA and is based on the MPA and SSA algorithms and uses Otsu’s method as an objective function. The proposed hybrid algorithm depends on boosting the performance of MPA via using the SSA.

The MPA is used to reduce the search region by determining the best solution; then, SSA optimizes each agent less than the limited base. Therefore, the ABCSCA algorithm starts by computing the histogram of an input image and then generates a random population of pop_size solutions (threshold values). Then, the MPA updates these populations using its levels representing by three faces of motion, then Eddy Formation and FADs’ Effect. The optimal solution is then determined from the population based on Otsu’s method (the best solutions from the MPA algorithm).

The SSA begins determining the minimum threshold value by using the MPA’s output (worst solution) and optimizing the solutions of the population via the strategy discussed before. The optimal global solution (the SSA algorithm’s output) is determined, and all the previous steps are repeated until the stopping conditions are met. The final stage of the MPASSA is illustrated in Fig. 3. It can be observed that the proposed method introduces an arithmetic complex which is $O (t (nd \text{Cof} * n))$, where $n$ represents a number of factors, $t$ is the iteration, $d$ is the problem dimension, and $\text{Cof}$ is the cost of function.

4 Experiments and results

In this part, the performance of the MPASSA is evaluated by two experiments (gray and colored). It is compared with five algorithms: original Marine Predators Algorithm MPA, original Salp Swarm Algorithm (SSA), Whale Optimization Algorithm (WOA), Particle Swarm Optimization (PSO), and Arithmetic Optimization Algorithm (AOA). Besides, two types of images are used to test the proposed method (2 grays and 3 color images). The parameters settings of the employed methods are taken from the original methods. The supplied results is expressed as the best fitness function, PSNR, and SSIM. Furthermore, for all of the acquired findings, the Friedman ranking test is used to demonstrate how significantly the suggested approach outperforms the comparable methods for all of the examined issues. The methods are developed and implemented in MATLAB (2015a) on a machine with the following specifications: CPU 2.3 GHz (an Intel Core i7 platform), 16 GB RAM, 2400 MHz, and DDR4.

4.1 Experimental settings

The comparison of all algorithms used in the research has the same cessation conditions (maximum iterations set to 100), with a total run of 30 per algorithm and the population’s size (25). For performance evaluation of all experiments on the test images are done by the number of thresholds: 2, 3, 4, and 5 as in [18]. The selection for such thresholds was to illustrate the performance of the proposed algorithm (MPASSA) compared with the traditional
4.2 Performance Measures

In order to evaluate the fitness of the segmented image, four measures are used. The measures that applied to the proposed algorithms, as follows:

1. The execution time.
2. The fitness value is calculated to evaluate and assess each solution based on its current position, as mentioned in chapter four.

3. The Peak Signal-to-Noise Ratio (PSNR) measure [51]: used to measure the variance between the reference image and segmented image, and it depends on the value of intensity in the image, and this refers to the fitness of the reconstructed image. The PSNR is defined as:

\[
PSNR = 20 \log_{10} \left( \frac{255}{RMSE} \right), \text{(in dB)}
\]  

RMSE refer to the root-mean-squared error, defined as:

\[
RMSE = \sqrt{\frac{\sum_{i=1}^{M} \sum_{j=1}^{Q} (I(i,j) - Seg(i,j))^2}{M \times Q}}
\]

\(I\) and \(Seg\) refer to the original and segmented images have a size \(M \times Q\), respectively. The maximum value of \(PSNR\) refers to the max performance of the segmentation algorithms.

4. The Structural Similarity Index (SSIM): is used to evaluate the similarity between \(I\) and \(Seg\) image, defined as:

\[
SSMI(I, Seg) = \frac{(2 \mu_I \mu_{Seg} + C_1)(2 \sigma_{I,Seg} + C_2)}{(\mu^2_I + \mu^2_{Seg} + C_1)(\sigma^2_I + \sigma^2_{Seg} + C_2)}
\]

\(\mu_I\) and \(\mu_{Seg}\) refer to mean intensity of \((I)\) and \((Seg)\) respectively; while \(\sigma_I\) and \(\sigma_{Seg}\) refer to standard deviation of \((I)\) and \((Seg)\) respectively; \(\sigma_{I,Seg}\) represent a variance of \((I)\) and \((Seg)\). \(c_1\) and \(c_2\) are constants, that \(c_1 = 6.5025\) and \(c_2 = 58.52252\) [36]. The maximum value of \(SSIM\) refers to better performance.

5. Friedman ranking test: The Friedman test is the non-parametric alternative to the one-way ANOVA with repeated measures. It is used to test for differences between groups when the dependent variable being measured is ordinal. It can also be used for continuous data that has violated the assumptions necessary to run the one-way ANOVA with repeated measures [7].

### 4.3 Parameters setting

Table 1 shows the parameters settings for each algorithm that are used in the following experiments. In addition, the general parameters are set as follows.

### 4.4 Benchmark images

This paper tested all algorithms on the five images: two gray images and three-color images. These images are from the dataset of Berkeley University [33], namely, lena, baboom for gray
4.5 The results and discussions

This section discusses the proposed hybrid MPASSA compared to other popular algorithms in the segmentation domain. The comparisons are conducted using several measures (i.e., fitness value, PSNR, SSIM, and time). Two grayscale of images and three-color images with four numbers of thresholds (2, 3, 4, and 5) are applied and compared the results with five comparative algorithms (i.e., MPA [25], SSA [34], WOA [1], PSO [15], and AOA [11])

| Algorithm | Parameters setting |
|-----------|-------------------|
| SSA [34]  | $c_2$ and $c_1$ are random value [1, 0] |
| MPA [24]  | $FAD_s=0.2, P=0.5$ |
| PSO [16]  | $wMax=0.9, wMin=0.2, c_1=2, c_2 =2$ |
| WOA [35]  | $a = [2.0], b=1, t [-1.1]$ |
| AOA [42]  | $Alpha=5, Mu=0.499$ |
| MPASSA    | $FAD_s=0.2, P=0.5$, |

images as shown in Fig. 4(a, b), and lena, baboom, and peppers for color images as shown in Fig. 5(a, b, c). With size (512 × 512) for all.
The results of the comparison are given in terms of PSNR, SSIM, CPU time, Fitness values, in addition to the Friedman ranking test for the comparative methods using the PSNR and SSIM Mean values for each image. These are standard performance evaluation measures in image segmentation, especially for evaluating multilevel thresholds methods. The discussion depends on each criterion are given as follows.

### Table 2 The best fitness values obtained from the algorithms on the gray images

| Image  | K   | WOA   | SSA   | AOA   | MPA   | PSO   | MPASSA |
|--------|-----|-------|-------|-------|-------|-------|--------|
| baboom | 2   | 2540.24 | 2540.321 | 2539.063 | 2561.349 | 2539.553 | 2564.773 |
|        | 3   | 2705.65 | 2705.093 | 2665.147 | 3429.821 | 2720.444 | 3441.869 |
|        | 4   | 2761.407 | 2771.824 | 2720.958 | 3811.454 | 2772.276 | 4320.183 |
|        | 5   | 2814.123 | 2796.225 | 2775.288 | 4706.062 | 2802.736 | 4732.528 |
| lena   | 2   | 1961.774 | 1961.801 | 1961.048 | 1970.247 | 1975.049 | 1978.61 |
|        | 3   | 2121.952 | 2128.221 | 2070.956 | 2686.071 | 2134.601 | 2698.594 |
|        | 4   | 2191.709 | 2186.528 | 2146.923 | 2693.825 | 2320.882 | 3217.882 |
|        | 5   | 2194.979 | 2210.997 | 2171.321 | 3555.501 | 2545.561 | 3763.314 |

### Table 3 The best fitness values obtained from the algorithms on the color images (Red color)

| Image   | K   | WOA   | SSA   | AOA   | MPA   | PSO   | MPASSA |
|---------|-----|-------|-------|-------|-------|-------|--------|
| lena    | 2   | 1759.116 | 1758.928 | 1745.142 | 1777.281 | 1775.373 | 1779.09 |
|         | 3   | 1885.357 | 1882.624 | 1830.816 | 2400.669 | 1884.819 | 2401.463 |
|         | 4   | 1916.914 | 1936.248 | 1851.609 | 2706.181 | 1938.726 | 2870.553 |
|         | 5   | 2344.27 | 2344.721 | 2325.878 | 4652.723 | 2418.37 | 4752.116 |
| baboom  | 2   | 2903.044 | 2902.255 | 2858.549 | 2916.941 | 2913.571 | 2917.897 |
|         | 3   | 3086.404 | 3060.594 | 2981.364 | 4390.888 | 3094.46 | 4419.153 |
|         | 4   | 3154.283 | 3153.333 | 3090.015 | 4840.728 | 3156.338 | 4973.319 |
|         | 5   | 3200.018 | 3201.987 | 3211.989 | 6248.24 | 3209.725 | 6237.732 |
| peppers | 2   | 1758.845 | 1755.602 | 1705.031 | 1778.65 | 1769.214 | 1778.743 |
|         | 3   | 1883.002 | 1847.382 | 1811.518 | 2362.56 | 1881.986 | 2405.533 |
|         | 4   | 1923.829 | 1918.6 | 1911.359 | 2538.1 | 1907.119 | 2898.64 |
|         | 5   | 1953.451 | 1955.783 | 1895.952 | 2859.001 | 1950.474 | 3228.724 |

### Table 4 The best fitness values obtained from the algorithms on the color images (Green color)

| Image | K   | WOA   | SSA   | AOA   | MPA   | PSO   | MPASSA |
|-------|-----|-------|-------|-------|-------|-------|--------|
| baboom | 2   | 2430.33 | 2434.255 | 2382.197 | 2467.48 | 2428.952 | 2469.495 |
|         | 3   | 2638.255 | 2645.489 | 2495.657 | 3249.076 | 2602.186 | 3254.056 |
|         | 4   | 2726.173 | 2727.67 | 2572.067 | 3565.544 | 2746.819 | 3636.873 |
|         | 5   | 2746.354 | 2731.698 | 2703.694 | 3896.637 | 2736.831 | 4318.764 |
| peppers | 2   | 2326.881 | 2328.222 | 2251.314 | 2348.447 | 2349.319 | 2351.324 |
|         | 3   | 2417.967 | 2417.967 | 2315.081 | 3051.351 | 2432.396 | 3244.085 |
|         | 4   | 2472.045 | 2483.902 | 2254.491 | 3146.329 | 2480.248 | 3584.116 |
|         | 5   | 2527.195 | 2483.655 | 2433.25 | 3722.265 | 2485.464 | 4033.038 |
| peppers | 2   | 5203.927 | 5203.927 | 5194.795 | 5233.783 | 5227.777 | 5235.423 |
|         | 3   | 5381.305 | 5374.99 | 5334.478 | 6916.685 | 5353.02 | 7354.29 |
|         | 4   | 5451.083 | 5447.217 | 5418.614 | 7628.84 | 5427.893 | 9026.392 |
|         | 5   | 5519.578 | 5509.297 | 5506.294 | 8698.647 | 5506.08 | 9259.896 |
Table 5  The best fitness values obtained from the algorithms on the color images (Blue color)

| Image | K  | WOA     | SSA     | AOA     | MPA     | PSO     | MPASSA  |
|-------|----|---------|---------|---------|---------|---------|---------|
| lena  |    | 1009.721| 1009.721| 727.3778| 1033.654| 1023.687| 1034.68  |
|       | 3  | 1069.997| 1036.101| 915.2615| 1231.034| 1038.308| 1384.995 |
|       | 4  | 1087.979| 1008.752| 1044.375| 1581.942| 1057.043| 1594.859 |
|       | 5  | 1103.255| 1106.493| 1079.437| 1659.359| 1150.208| 1816.25  |
| baboom| 2  | 4005.208| 4005.208| 4003.659| 4029.964| 4011.061| 4030.464 |
|       | 3  | 4203.425| 4203.425| 4136.449| 4882.566| 4218.451| 5927.24  |
|       | 4  | 4292.959| 4244.282| 4167.025| 5844.418| 4311.669| 6536.206 |
|       | 5  | 4328.937| 4297.179| 4291.278| 6677.484| 4368.803| 7257.704 |
| peppers| 2 | 1656.159| 1656.201| 1503.631| 1667.147| 1669.945| 1672.346 |
|       | 3  | 1765.681| 1776.796| 1652.439| 2085.579| 1697.584| 2148.473 |
|       | 4  | 1848.924| 1793.298| 1762.796| 2085.936| 1847.228| 2620.117 |
|       | 5  | 1878.877| 1879.04 | 1785.778| 2709.747| 1851.902| 3019.093 |

Fig. 6  Fitness values of baboom image

Fig. 7  Fitness values of lena image
Fig. 8  Fitness values of color images. R is red, G is green, B is blue. And 1 is lena, 2 is baboom, 3 is peppers images
The fitness function values of all algorithms are mentioned and analyzed over the thresholds’ variance. Tables 2, 3, 4 and 5 show the average fitness function values for the gray, red, green, blue images, where the threshold value is 2 for all algorithms. The proposed algorithm got better results in comparison with all the comparative algorithms. Whereas in levels 3, 4, and 5, the percentage of the difference is considerable between the MPASSA and other algorithms, as shown in Figs. 6 and 7 for grayscale images. Figure 8 shows the fitness values of the comparative methods for the different colored images. These results show the superiority of the MPASSA at the large threshold values.

In terms of PSNR measure, the testing results of the threshold two as in Tables 6 and 7, the MPASSA got the best results in all images (gray and color) followed by MPA at some times which got the best results, followed by WOA, PSO, SSA, and AOA. The results of threshold 2 indicate that the MPASSA obtained the best values in all images. The MPASSA outperformed all other algorithms in thresholds 3, 4, and 5. It achieved the best results in all images, followed by the WOA, MPA, PSO, and SSA. From the results, we can derive that MPASSA is the best algorithm according to the PSNR measure, followed by MPA and WOA, and these algorithms outperformed the others when the threshold is greater than 4.
In Tables 8 and 9, the comparative algorithms’ results are presented in terms of SSIM for gray and color images, respectively. According to the results obtained by applying two thresholds, the proposed MPASSA got the best results in all images (i.e., gray and color), followed by SSA, which got the best results in 3 images out of 5, while the values of each
AOA, MPA, WOA and PSO algorithms are comparative according to the tested images. At the threshold level 3, the proposed MPASSA method obtained the best results in all images, followed by MPA, WOA, SSA, and AOA. Also, at the threshold levels 4 and 5, the proposed method obtained the best results in all images. Simultaneously, each WOA, SSA, AOA, PSO, and MPA are similar according to the SSIM values. From these results, we can conclude that MPASSA is the best algorithm among all comparative algorithms.

The CPU time is considered for all algorithms and listed in Tables 10 and 11 to show all algorithms’ performance in terms of exhaustion time. To compare the time complexity of the proposed MPASSA method against other algorithms, Table 10 presents the CPU time for the gray level, and Table 11 presents the CPU time for the color images. These tables illustrated that the proposed method consuming average time between the other algorithms. It was ranked fourth, better than MPA and PSO algorithms, and worse than SSA, AOA, and WOA. While SSA was the lowers consuming of time execution followed by AOA and then WOA at all levels with all images (gray and color).

The Friedman ranking test results using PSNR and SSIM for all the tested methods using different tested images (gray and color) are given in Tables 12, 13, 14, 15, 16, 17, 18, 19, 20...
and 21. The Tables show the rank of each method, summation, mean ranking, and the final ranking.

For the gray images, in Table 12 of PSNR value, the MPASSA got the first ranking followed by WOA, it got the second-ranking, and SSA has the third ranking. Simultaneously,
the AOA and PSO ranked fourth, and MPA got the last ranking. These results proved the ability of the proposed MPASSA in solving the image segmentation problem. In Table 13 of the PSNR value, the MPASSA and SSA got the first ranking followed by AOA; it got the second-ranking, MPA has the third ranking. In contrast, WOA got the fourth ranking, and PSO has the fifth the last ranking in the table. This result illustrated that the proposed MPASSA has a promising outcome compared to other methods.

### Table 10  
Average CPU time (seconds) for gray images

| K  | WOA  | SSA  | AOA  | MPA  | PSO  | MPASSA |
|----|------|------|------|------|------|--------|
| Lena | 2  | 0.251967 | 0.245896 | 0.239373 | 5.940693 | 1.146158 | 1.91396 |
| 3  | 0.232458 | 0.228359 | 0.230218 | 7.630269 | 1.79152 | 2.651281 |
| 4  | 0.241309 | 0.231332 | 0.238687 | 5.203141 | 2.080605 | 3.733159 |
| 5  | 0.25015 | 0.245332 | 0.247421 | 11.48492 | 2.594214 | 4.058729 |
| baboom | 2  | 0.311161 | 0.245086 | 0.248864 | 2.90873 | 0.723672 | 2.736707 |
| 3  | 0.291892 | 0.263487 | 0.249791 | 4.504445 | 1.12395 | 4.09117 |
| 4  | 0.309512 | 0.303814 | 0.263115 | 10.71171 | 1.121382 | 4.379006 |
| 5  | 0.31204 | 0.259287 | 0.266202 | 5.274792 | 1.188409 | 5.35945 |

### Table 11  
Average CPU time (seconds) for color images

| K  | WOA  | SSA  | AOA  | MPA  | PSO  | MPASSA |
|----|------|------|------|------|------|--------|
| Lena | 2  | 0.040097 | 0.03062 | 0.036374 | 76.88261 | 11.06229 | 6.020129 |
| 3  | 0.044229 | 0.035656 | 0.043114 | 106.065 | 15.30059 | 7.626052 |
| 4  | 0.112027 | 0.064104 | 0.077583 | 175.7069 | 27.53357 | 16.09753 |
| 5  | 0.113222 | 0.082588 | 0.091326 | 140.0356 | 26.58181 | 13.93868 |
| baboom | 2  | 2.307623 | 0.087376 | 0.079854 | 22.60579 | 3.105797 | 9.946913 |
| 3  | 0.061295 | 0.047198 | 0.054166 | 101.672 | 17.13897 | 7.643711 |
| 4  | 0.061844 | 0.045043 | 0.054286 | 129.8905 | 23.27711 | 10.81031 |
| 5  | 0.082559 | 0.077439 | 0.081497 | 28.96452 | 6.030701 | 20.01818 |
| peppers | 2  | 0.055243 | 0.042374 | 0.050997 | 79.58729 | 10.50436 | 6.968161 |
| 3  | 0.043226 | 0.038953 | 0.046059 | 105.7169 | 17.60654 | 9.140672 |
| 4  | 0.05905 | 0.041318 | 0.049201 | 131.4959 | 23.11287 | 10.81287 |
| 5  | 0.058529 | 0.046055 | 0.058149 | 21.57042 | 32.8968 | 13.90128 |

### Table 12  
The results of the Friedman ranking test for the comparative methods using the PSNR values for image Lena

| PSNR | K  | MPASSA | WOA  | SSA  | AOA  | PSO  | MPA  |
|------|----|--------|------|------|------|------|------|
| Lena | 2  | 2      | 5    | 4    | 1    | 3    | 6    |
| 3    | 5    | 1      | 3    | 6    | 4    | 2    |
| 4    | 1    | 3      | 2    | 5    | 4    | 6    |
| 5    | 1    | 2      | 3    | 5    | 6    | 4    |
| SUM  | 9    | 11     | 12   | 17   | 17   | 18   |
| Mean rank | 2.25 | 2.75  | 3    | 4.25 | 4.25 | 4.5  |
| Final Rank | 1    | 2     | 3    | 4    | 4    | 5    |
### Table 13
The results of the Friedman ranking test for the comparative methods using the PSNR values for image baboom

| PSNR | K | MPASSA | WOA | SSA | AOA | PSO | MPA |
|------|---|--------|-----|-----|-----|-----|-----|
| Baboom | 2 | 4 | 5 | 1 | 2 | 6 | 3 |
| 3    | 4 | 6 | 1 | 5 | 3 | 2 |
| 4    | 1 | 3 | 2 | 4 | 6 | 5 |
| 5    | 1 | 2 | 6 | 3 | 4 | 5 |
| SUM  | 10 | 16 | 10 | 14 | 19 | 15 |
| Mean rank | 2.5 | 4 | 2.5 | 3.5 | 4.75 | 3.75 |
| Final Rank | 1 | 4 | 1 | 2 | 5 | 3 |

### Table 14
The results of the Friedman ranking test for the comparative methods using the PSNR values for image lena

| PSNR | K | MPASSA | WOA | SSA | AOA | PSO | MPA |
|------|---|--------|-----|-----|-----|-----|-----|
| Lena | 2 | 4 | 5 | 1 | 6 | 2 | 3 |
| 3    | 3 | 1 | 4 | 6 | 5 | 2 |
| 4    | 2 | 3 | 5 | 1 | 4 | 6 |
| 5    | 1 | 3 | 2 | 6 | 5 | 4 |
| SUM  | 10 | 12 | 12 | 19 | 16 | 15 |
| Mean rank | 2.5 | 3 | 3 | 4.75 | 4 | 3.75 |
| Final Rank | 1 | 2 | 2 | 5 | 4 | 3 |

### Table 15
The results of the Friedman ranking test for the comparative methods using the PSNR values for image baboom

| PSNR | K | MPASSA | WOA | SSA | AOA | PSO | MPA |
|------|---|--------|-----|-----|-----|-----|-----|
| baboom | 2 | 1 | 5 | 3 | 2 | 4 | 6 |
| 3    | 2 | 3 | 4 | 6 | 1 | 5 |
| 4    | 1 | 4 | 3 | 6 | 2 | 5 |
| 5    | 2 | 4 | 3 | 6 | 1 | 5 |
| SUM  | 6 | 16 | 13 | 20 | 8 | 21 |
| Mean rank | 1.5 | 4 | 3.25 | 5 | 2 | 5.25 |
| Final Rank | 1 | 4 | 3 | 5 | 2 | 6 |

### Table 16
The results of the Friedman ranking test for the comparative methods using the PSNR values for image peppers

| PSNR | K | MPASSA | WOA | SSA | AOA | PSO | MPA |
|------|---|--------|-----|-----|-----|-----|-----|
| peppers | 2 | 2 | 3 | 1 | 6 | 5 | 4 |
| 3    | 2 | 6 | 3 | 4 | 5 | 1 |
| 4    | 1 | 6 | 4 | 3 | 5 | 2 |
| 5    | 1 | 6 | 3 | 2 | 4 | 5 |
| SUM  | 6 | 21 | 11 | 15 | 19 | 12 |
| Mean rank | 1.5 | 5.25 | 2.75 | 3.75 | 4.75 | 3 |
| Final Rank | 1 | 6 | 2 | 4 | 5 | 3 |
### Table 17
The results of the Friedman ranking test for the comparative methods using the SSIM values for image lena

| SSIM | K | MPASSA | WOA | SSA | AOA | PSO | MPA |
|------|---|--------|-----|-----|-----|-----|-----|
| Lena | 2 | 1      | 5   | 4   | 2   | 3   | 6   |
|      | 3 | 3      | 1   | 2   | 6   | 4   | 5   |
|      | 4 | 1      | 4   | 6   | 5   | 2   | 3   |
|      | 5 | 3      | 4   | 2   | 6   | 1   | 4   |
| SUM  | 8 | 14     | 14  | 19  | 11  | 18  |
| Mean rank | 2 | 3.5   | 3.5 | 4.75 | 2.75 | 4.5 |
| Final Rank | 1 | 3     | 3   | 5   | 2   | 4   |

### Table 18
The results of the Friedman ranking test for the comparative methods using the SSIM values for image baboom

| SSIM | K | MPASSA | WOA | SSA | AOA | PSO | MPA |
|------|---|--------|-----|-----|-----|-----|-----|
| Baboom | 2 | 2      | 5   | 1   | 3   | 6   | 4   |
|      | 3 | 4      | 6   | 1   | 5   | 3   | 2   |
|      | 4 | 1      | 4   | 2   | 3   | 6   | 5   |
|      | 5 | 1      | 2   | 6   | 5   | 3   | 4   |
| SUM  | 8 | 17     | 10  | 16  | 18  | 15  |
| Mean rank | 2 | 4.25  | 2.5 | 4   | 4.5 | 3.75 |
| Final Rank | 1 | 5     | 2   | 4   | 6   | 3   |

### Table 19
The results of the Friedman ranking test for the comparative methods using the SSIM values for image lena

| SSIM | K | MPASSA | WOA | SSA | AOA | PSO | MPA |
|------|---|--------|-----|-----|-----|-----|-----|
| Lena | 2 | 3      | 4   | 1   | 6   | 2   | 5   |
|      | 3 | 4      | 1   | 2   | 6   | 5   | 3   |
|      | 4 | 2      | 3   | 4   | 1   | 5   | 6   |
|      | 5 | 1      | 3   | 4   | 6   | 5   | 2   |
| SUM  | 10 | 11    | 11  | 19  | 17  | 16  |
| Mean rank | 2.5 | 2.75 | 2.75 | 4.75 | 4.25 | 4 |
| Final Rank | 1 | 2     | 2   | 5   | 4   | 3   |

### Table 20
The results of the Friedman ranking test for the comparative methods using the SSIM values for image baboom

| SSIM | K | MPASSA | WOA | SSA | AOA | PSO | MPA |
|------|---|--------|-----|-----|-----|-----|-----|
| Baboom | 2 | 1      | 5   | 3   | 2   | 4   | 6   |
|      | 3 | 1      | 3   | 4   | 5   | 2   | 6   |
|      | 4 | 1      | 5   | 2   | 6   | 3   | 4   |
|      | 5 | 1      | 4   | 3   | 5   | 2   | 6   |
| SUM  | 4 | 17     | 12  | 18  | 11  | 22  |
| Mean rank | 1 | 4.25  | 3   | 4.5 | 2.75 | 5.5 |
| Final Rank | 1 | 4     | 3   | 5   | 2   | 6   |
Tables 14, 15 and 16 shows the ranking results based on using PSNR values for color images. In Table 14, the MPASSA got the first ranking, followed by each of WOA and SSA, which have got the second-ranking, MPA has the third-ranking. In contrast, PSO has the fourth-ranking, and AOA got the last ranking in the table. In Table 15, the MPASSA got the first ranking followed by PSO; it got the second-ranking, SSA has the third-ranking, while

| SSIM | K   | MPASSA | WOA | SSA | AOA | PSO | MPA |
|------|-----|--------|-----|-----|-----|-----|-----|
| peppers | 2 | 1 | 5 | 2 | 6 | 4 | 3 |
| 3 | 1 | 6 | 2 | 3 | 5 | 4 |
| 4 | 1 | 2 | 5 | 6 | 4 | 3 |
| 5 | 2 | 6 | 1 | 3 | 4 | 5 |
| SUM | 5 | 19 | 10 | 18 | 17 | 15 |
| Mean rank | 1.25 | 4.75 | 2.5 | 4.5 | 4.25 | 3.75 |
| Final Rank | 1 | 6 | 2 | 5 | 4 | 3 |

Fig. 9  Segmented lena gray images using Otsu’s (a2–f2) represent threshold2, (a3–f3) represent threshold3, (a4–f4) represent threshold4, (a5–f5) represent threshold5

Tables 14, 15 and 16 shows the ranking results based on using PSNR values for color images. In Table 14, the MPASSA got the first ranking, followed by each of WOA and SSA, which have got the second-ranking, MPA has the third-ranking. In contrast, PSO has the fourth-ranking, and AOA got the last ranking in the table. In Table 15, the MPASSA got the first ranking followed by PSO; it got the second-ranking, SSA has the third-ranking, while
WOA got the fourth-ranking, followed by AOA has the fifth ranking, and MPA at the last ranking in the table. In Table 16, the MPASSA got the first ranking, followed by SSA. It got the second-ranking, MPA has the third-ranking, while AOA got the fourth-ranking, followed by PSO have the fifth ranking and WOA at the last ranking in the table. The given results revealed that the modified version of MPA using SSA got better results than other comparative methods and avoided the basic version of MPA’s weaknesses.

For the gray images in Table 17 of SSIM value, the MPASSA got the first ranking followed by PSO; it got the second-ranking, each of WOA and SSA has the third-ranking. In contrast, MPA has the fourth-ranking, and AOA got the last ranking. In Table 18 of SSIM value, the MPASSA got the first ranking followed by SSA; it got the second-ranking, MPA has the third-ranking. In contrast, AOA got the fourth-ranking, and WOA has the fifth ranking and PAO at the last ranking. This result illustrated that the proposed MPASSA has a better performance compared to other methods.

In Table 19, the MPASSA got the first ranking for the color images, followed by SSA, which got the second-ranking with WOA. At the same time, MPA has the third-ranking, and PSO got the fourth-ranking, and at the end ranking, AOA has the last ranking. In Table 20, the MPASSA got the first ranking followed by PSO; it got the second-ranking, SSA has the third-

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**Fig. 10** Segmented *baboom* gray images using Otsu’s $(a_2–f_2)$ represent threshold2, $(a_3–f_3)$ represent threshold3, $(a_4–f_4)$ represent threshold4, $(a_5–f_5)$ represent threshold5
ranking, while WOA got the fourth-ranking, followed by AOA has the fifth ranking and MPA at the last ranking. In Table 21, the MPASSA got the first ranking, followed by SSA; it got the second-ranking, MPA has the third-ranking, while PSO got the fourth-ranking, followed by AOA has the fifth ranking, and WOA at the last ranking. The given results showed that the proposed version of MPA using SSA got promising results compared to other comparative methods and avoided the basic version of MPA.

Figures 9, 10, 11, 12, and 13 show the segmented test images (gray and color) obtained by the comparative methods using various threshold values (k= 2, 3, 4, and 5). The proposed MPASSA got the best-segmented images compared to other comparative methods. Figure 14 shows the gray and color images histogram distribution estimated by the proposed hybrid algorithm MPASSA at k equal to 2, 3, 4, and 5.

The proposed MPASSA got the optimum results in most cases. This because each of the images is considered as a varied optimization problem. Moreover, because of the randomness of the swarm methods, the results can change in some cases. Also, depending on No-Free Lunch Theorem NFL that illustrates, it is hard to find one algorithm suitable for many optimization problems. As well as, each image has a varied gray or colored level histogram. Also, image segmentation becomes a complex operation due to

![Fig. 11 Segmented lena color images using Otsu’s (a2–f2) represent threshold2, (a3–f3) represent threshold3, (a4–f4) represent threshold4, (a5–f5) represent threshold5](image-url)
the histogram’s multimodality. The segmented image is constructed by determining each class a grey or the colored level value specified from the class members’ mean. So, for each image, the proposed MPASSA performed better in terms of the PSNR, SSIM, and fitness values at each level. The MPASSA may fail to segment the image in some cases and at different levels. For these reasons, we used statistical comparisons to determine the best algorithm for several images.

5 Conclusion and future work

Multilevel thresholding is one of the methods used in image segmentation. It is considered a preprocessing phase in many applications. In this research, the problem of defining the optimal/ best threshold for image segmentation in the case of multilevel thresholding. This problem has been considered as an ‘optimization problem’. Otsu’s function has been applied as a fitness function. So, a novel hybrid algorithm in image segmentation of multilevel threshold was proposed. It draws from the properties of both Marine Predators and Salp Swarm algorithms. The proposed algorithm has been used to solve this problem. Each one aims to define the optimal threshold value, which increases Otsu’s function. The proposed
novel algorithm results have been compared with MPA, SSA, WOA, AOA, and PSA algorithms. The performance of algorithms has been evaluated based on the following measures: fitness values, Peak Signal-to-Noise Ratio (PSNR), Structural Similarity Index (SSIM), CPU-time, and Friedman ranking test. We used five benchmark images for gray and color images in all experiments.

The study concluded that the proposed hybrid MPASSA method’s performance is better than that of the MPA and SSA algorithms and other algorithms. The leading cause for this supremacy is that hybrid technology combines the characteristics of different methods. Therefore, the proposed hybrid algorithm averts getting stuck on a local optimum. All of this indicates that hybrid techniques have a high ability to find the optimal solution for the image segmentation problem.

The proposed method can solve various problems and applications as of image processing, such as visualization, computer vision, computer-aided diagnostics, image classification, etc. In all of these applications, the finesses of images are a critical problem in image segmentation. Low resolutions, high noises, or lower contrast, can cause this problem. So, the preprocessing of the images is an essential point to improve the quality of that status and multi-objective cases to gain optimal segmentation results. Other recent optimizers, such as Arithmetic Optimization Algorithm (AOA), can solve the given problem with new modifications in the future.
Fig. 14  Gy and Color images histogram at K=2, 3, 4, 5 obtained by MPASSA

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Data availability

Declarations

Conflict of interest  The authors declare no conflict of interest.

Human and animal rights  This article does not contain any studies with human participants performed by any of the authors. No animal studies were carried out by the authors for this article.
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