



# Boosting whale optimization with evolution strategy and Gaussian random walks: an image segmentation method

Abdelazim G. Hussien<sup>1,2</sup> · Ali Asghar Heidari<sup>3</sup> · Xiaojia Ye<sup>4</sup> · Guoxi Liang<sup>5</sup> · Huiling Chen<sup>3</sup> · Zhifang Pan<sup>6</sup>

Received: 18 January 2021 / Accepted: 27 October 2021 / Published online: 27 January 2022  
© The Author(s), under exclusive licence to Springer-Verlag London Ltd., part of Springer Nature 2021

## Abstract

Stochastic optimization has been found in many applications, especially for several local optima problems, because of their ability to explore and exploit various zones of the feature space regardless of their disadvantage of immature convergence and stagnation. Whale optimization algorithm (WOA) is a recent algorithm from the swarm-intelligence family developed in 2016 that attempts to inspire the humpback whale foraging activities. However, the original WOA suffers from getting trapped in the suboptimal regions and slow convergence rate. In this study, we try to overcome these limitations by revisiting the components of the WOA with the evolutionary cores of Gaussian walk, CMA-ES, and evolution strategy that appeared in Virus colony search (VCS). In the proposed algorithm VCSWOA, cores of the VCS are utilized as an exploitation engine, whereas the cores of WOA are devoted to the exploratory phases. To evaluate the resulted framework, 30 benchmark functions from IEEE CEC2017 are used in addition to four different constrained engineering problems. Furthermore, the enhanced variant has been applied in image segmentation, where eight images are utilized, and they are compared with various WOA variants. The comprehensive test and the detailed results show that the new structure has alleviated the central shortcomings of WOA, and we witnessed a significant performance for the proposed VCSWOA compared to other peers.

**Keywords** Exploration and exploitation · Nature-inspired method · Metaheuristic · Optimization algorithms · Engineering problems

## 1 Introduction

In the last 2 decades, many metaheuristic algorithms have been proposed by researchers due to their advantages like flexibility, bypassing local optima, and they did not need gradient information [1]. Metaheuristics algorithms have gained huge attention and a significant interest as they can solve real-world optimization problems by mathematically

simulating physical/biological phenomena. They have been applied to many problems [2, 3]. These algorithms can be divided into four major categories: I(EAs), Swarm Intelligence-based algorithm (SI-based), physics & chemistry algorithms, and Human-based Algorithm. The first category (evolutionary algorithms) contains algorithms inspired by natural evolution. In EAs, there is a randomly generated population at first to start. Then, all individuals are evaluated

✉ Guoxi Liang  
guoxiliang2017@gmail.com

✉ Huiling Chen  
chenhuiling.jlu@gmail.com

✉ Zhifang Pan  
panzhifang@wmu.edu.cn

Abdelazim G. Hussien  
abdelazim.hussien@liu.se; aga08@fayoum.edu.eg

Ali Asghar Heidari  
aliasghar68@gmail.com

Xiaojia Ye  
yxj@lixin.edu.cn

<sup>1</sup> Department of Computer and Information Science, Linköping University, Linköping, Sweden

<sup>2</sup> Faculty of Science, Fayoum University, Fayoum, Egypt

<sup>3</sup> Department of Computer Science and Artificial Intelligence, Wenzhou University, Wenzhou 325035, People's Republic of China

<sup>4</sup> Shanghai Lixin University of Accounting and Finance, Shanghai 201209, People's Republic of China

<sup>5</sup> Department of Information Technology, Wenzhou Polytechnic, Wenzhou 325035, People's Republic of China

<sup>6</sup> The First Affiliated Hospital of Wenzhou Medical University, Wenzhou 325000, People's Republic of China

over a generation to produce new individuals using crossover and mutation processes. This category includes genetic algorithms (GA) [4], evolution simulation strategy (ES) [5], genetic programming (GP) [6], and biogeography-based optimizer (BBO) [1].

The second category is SI-based algorithms inspired by swarms' social behavior [7], a collection of living beings in nature. Examples of SI algorithms are particle swarm algorithm (PSO) [8], ant colony optimization [9], Harris hawks optimizer (HHO) [10], virus colony search [11], slime mould algorithm (SMA) [12], Hunger games search (HGS) [13], and Runge–Kutta (RUN) optimizer [14]. The third class includes algorithms that simulate physical or chemical phenomena. Examples of this class are simulated annealing (SA) [15], and gravitational search algorithm (GSA) [16]. The last class includes algorithms, which are inspired by human behavior like teaching learning-based optimization (TLBO) [17] and tabu (Taboo) search (TS) [18]. In addition to engineering optimization problems [19, 20], these stochastic methods have found their applications and contributions in more complex problems and attracted many works in science and engineering fields such as medical data classification [21–24], scheduling problems [25, 26], feature selection [27–29], wind speed forecast [30], engineering design problems [31–33]. Furthermore, potential of metaheuristics is not limited to such problems and still much room to discover in the fields of hard maximum satisfiability problem [34, 35], bankruptcy prediction [36, 37], parameter optimization [38–40], PID control [41–43], detection of foreign fiber in cotton [44, 45], surveillance [46], service ecosystem [47, 48], micro-expression spotting [49, 50], and prediction problems in educational ground [51, 52].

WOA is a recent algorithm developed by the author in [53] that has gained huge attention due to its simple code and high similarity with grey wolf optimizer (GWO). This algorithm can outperform many state-of-the-art algorithms such as GSA, PSO, and GA. This algorithm is based on the humpback special hunting behavior, which is called the bubble net method. WOA has received huge interest and global attention since its inception, as it shows a good performance in handling many optimization tasks. Consequently, some modifications have been made by many researchers. In [54], they proposed a binary version of WOA using two transfer functions. The new versions applied to solve travel salesman problem (TSP). In [55], Aljarah et al. used WOA to find the optimal connecting weights in a neural network. Also, Elaziz et al. [56] developed a hyper-heuristic algorithm by using DE to improve the initial WOA population. In [57], Emary et al. tried to study the impact of levy flight in WOA and SCA. Likewise, Oliva et al. [58] proposed a new version of WOA using chaotic maps and applied it to estimate photovoltaic cell parameters. In [59], Xiong et al. proposed an improved version of WOA by developing two prey search

strategies. In [60], Chen et al. proposed two strategies based on Lévy flight and chaotic local search to have a good balance between the core capacities. Also, authors in [61] introduced a hybrid version of WOA and SA by embedding SA in WOA as a local search strategy. In [62], Abdel-Basset et al. designed a new version of WOA and used it in Cryptanalysis in Merkle–Hellman Cryptosystem. Another hybrid version between WOA and GWO called WGC is introduced to cluster data [63]. Agrawal et al. [64] applied embedded quantum operators in WOA and used it in the feature selection problem. Authors in [65] proposed a new version using an opposition-based technique to prevent the basic whale method on from getting trapped in local optima. Also, in works of [66, 67], the proposed approach was applied to the feature selection problem. In [68], Hemasian-Etefagh et al. tried to prevent the classical WOA from trapping into local optima by introducing a new version called group WOA (GWOA), in which the population was divided into many groups based on their fitness value. In [69], Hassib et al. proposed a novel classification framework for big data using the WOA. To solve job shop scheduling problems (JSSP), [70] tried to solve it by introducing a hybrid algorithm called (WOA-LFDE) in which differential evolution (DE), and Lévy flight are hybridized with WOA. Also, in [71], Jiang et al. introduced an enhanced WOA by embodying two approaches: introducing an armed force program and adjusting beneficial strategy. In [72], Guo et al. used a modified version of WOA by using the adaptive strategy of the neighborhood to forecast the demand for water resources. Also, in [73], Got et al. introduced an enhanced multi-objective version of WOA called guided population archive WOA (GPAWOA) to solve multi-objective problems.

WOA has been applied to many medical applications. Authors in [39] developed a chaotic multi-swarm WOA version called CMWOA using a support vector machine (SVM) and applied it to perform feature selection to many well-known and common medical diseases problems such as breast cancer, erythemato-squamous, and diabetes. Also, in [74], Abdel-Basset et al. integrated the basic WOA with TS and employed it to solve the quadratic assignment problem (Locating departments of the hospital). In [75], Tharwat et al. used WOA with SVM to be able to classify the biotransformed toxicity effects of hepatic drugs. Also, in [76], Zhao et al. mixed SVM kernel function with WOA to classify colorectal cancer diagnosis.

Gharehchopogh and Gholizadeh listed all WOA variants and applications with details in a comprehensive survey [77]. Despite the original WOA success, many works showed that its performance might degrade when solving some optimization tasks.

On the other hand, another recent metaheuristic called virus colony search (VCS) was developed [11]. VCS simulates viruses diffusion and infection behavior in attacking

cells. VCS has been applied to many power optimization problems such as unit commitment [78], resource allocation [79], and distributed generators placement [80].

In this study, a new enhanced WOA-based algorithm is designed that embedded the core mechanisms of VCS into the main method. It aims to overcome these limitations by revisiting the WOA based on the core components of the Gaussian walk, CMA-ES, and evolution strategy that appeared in the VCS. This could prevent WOA from getting trapped into local optima by maintaining a better balance among the exploration and exploitation capabilities. To evaluate the resulted framework, 30 benchmark cases from IEEE CEC2017 were employed in addition to four different constrained engineering problems. Besides, the enhanced WOA-based variant has been applied to image segmentation, where eight images are utilized, and they are compared with various WOA variants. The attained results show that the new structure has alleviated the central shortcomings of WOA, and we saw a significant performance for the proposed VCSSWOA compared to other peers.

This paper is organized as follows. Sections 2 and 3 give a detailed description and mathematical equations to the WOA and VCS, respectively. Sections 4 and 5 show the proposed method and results discussions. Section 6 concludes the paper.

## 2 Whale optimization algorithm

In this section, we present the basics of the WOA by describing its main components, such as inspiration, its mathematical model, and how it deals with exploration and exploitation. The WOA [53] introduced by Mirjalili et al. in 2016, which mimics the foraging of humpback whales. Whales are beautiful creatures that have a special hunting technique called bubble-net feeding or 9-shape. Then, other agents attempt to change their location vector to attain the best position according to Eq. (1).

$$D = |C \cdot X^*(t) - X(t)| \tag{1}$$

$$X(t + 1) = X^*(t + 1) - A \cdot D \tag{2}$$

where  $t$  denotes the counter of iteration,  $C$  and  $A$  are coefficient vectors,  $X^*$  means the position vector of the best agent, and  $X$  is the location vector.  $A$  and  $C$  values are obtained from the following rules:

$$A = 2 \cdot a \cdot r - a \tag{3}$$

$$C = 2 \cdot r, \tag{4}$$

where  $a$  is linearly decreased from 2 to 0 over iterations and  $r$  randomly bounded in  $[0,1]$ . To mathematically simulate the exploitation phase, we have two approaches (1) Shrinking encircling: attained by decreasing a value's with regard to Eq. (4). Note that  $A$  is a random value between  $[-a, a]$ . (2) Spiral updating: this phase realizes the distance between the whale and the prey. Equation (5), calculates the spiral that mimics the helix-shaped movement as follow:

$$X(t + 1) = D^l \cdot e^{bl} \cdot \cos(2\pi l) + X^*(t), \tag{5}$$

where  $b$  is constant,  $l$  is a random number in  $[-1, 1]$ . To select either spiral moves or shrinking encircling phase, a chance of 50% is assumed as follow:

$$X(t + 1) = \begin{cases} X^*(t) - A \cdot D & \text{if } p < 0.5 \\ D^l \cdot e^{bl} \cdot \cos(2\pi l) + X^*(t) & \text{if } p \geq 0.5, \end{cases} \tag{6}$$

where  $p$  is a random number in a uniform distribution. In other hand side, in exploration (diversification) stage,  $1 < A < -1$  is used to force the solution to move away from this location. Equations (7) and (8), represent the mathematical for exploration phase as follow:

$$D = |C \cdot X_{rand} - X| \tag{7}$$

$$X(t + 1) = X_{rand} - A \cdot D \tag{8}$$

The general pseudo-code steps of WOA are presented in Algorithm 1.

**Algorithm 1** Whale Optimization Algorithm.

---

**Input:**  $n$  Number of whales in the population.  
**MaxIter** Number of iteration for Optimization  
**Output:** Optimal whale position  
Initialize a the population of  $n$  whales  
Find  $X^* = best$  search agent threads  
**while** stopping criteria not meet to **do**  
  **for**  $whale_i$  belong to whales **do**  
    Calculate and Update  $a$ ;  $A$ ,  $C$ ,  $p$  and  $l$ .  
    **if**  $p < 0.5$  **then**  
      **if**  $(|A| < 1)$  **then**  
        Update position by Eq. (2)  
      **else**  $(|A| \geq 1)$   
        Select a random search agent ( $X_{rand}$ )  
        Update position by Eq. (8)  
      **end if**  
    **else**  $(p \geq 0.5)$   
      Update position by Eq. (4)  
    **end if**  
    Update  $\mathbf{X}(t + 1)$  from Eq. (5)  
  **end for**  
  Check if any search agent goes beyond the search space  
  Calculate the fitness of each search agent  
  Update  $X^*$  if there is a better solution  
**end while**

---

### 3 Virus colony optimization algorithm

Virus colony search (VCS) is a novel population algorithm inspired by nature, which simulates infection and diffusion techniques. VCS mainly depends on three strategies: (1) Gaussian walk, (2) CMA-ES, and (3) evolution strategy.

The population is divided into two groups:  $V_{pop}$  which refers to virus colony, and  $H_{pop}$ , which refers to host cell colony. A host cell is infected by one virus. Then, the virus must obtain nutrients by destroying the host cell to be able to reproduce. Finally, the few best viruses remain in the next generation, and the other viruses are evolved. The following subsections simulate these steps mathematically.

#### 3.1 Viruses diffusion

A random walk is needed in this phase to simulate virus moving. Gaussian random walk (GRW) is used since it has a good performance as given in Eq. (9).

$$V_{pop_i} = \text{Gaussian}(G_{best}^g, \tau) + (r_1 \cdot G_{best}^g - r_2 \cdot V_{pop_i}), \quad (9)$$

where  $i$  refers to a random value and equals  $1, 2, 3, \dots, N$  where  $N$  is the size of the population,  $r_1$  &  $r_2$  are random variables and falls in the interval  $[0, 1]$ , and  $\tau$  refers to the standard deviation and can be calculated as follows:

$$\tau = \log(g)/g \cdot (V_{pop_i} - G_{best}^g). \quad (10)$$

In Eq. (9), the term  $(r_1 \cdot G_{best}^g - r_2 \cdot V_{pop_i})$  is used as a search direction in order to prevent direction from getting trapped in

a local optimum. Also, the term  $\log(g)/g$  is used to decrease Gaussian jump size over generations to improve the local search performance.

#### 3.2 Host cells infection

In this stage, the virus invades the host cell and tries to destroy it until its death. Then, the virus interacts with the host cell by absorbing essential nutrition and metabolizing harmful substances. Then, the host cell will be converted into a new virus. This process is used to improve the capabilities of the exploration process and observe the exchange of information. Hence, covariance matrix adaptation evolution strategy (CMA-ES) can be used to model derivative-free and stochastic optimization. The main steps to mathematically simulate this stage is as follows:

**Step 1:**  $H_{pop}$  updating process using Eq. (11).

$$H_{pop_i}^g = \left( \frac{\sum_i^N V_{pop_i}}{N} \right) + \sigma_i^g \times N_i(0, c_g) \quad (11)$$

where  $N_i(0, c_g)$  refers to the normal distribution with mean 0 and  $D \times D$  covariance matrix  $c_g$ .  $D$  refers to problem dimension,  $g$  refers to the current iteration.

**Step 2:** Selection of the best  $\lambda$  from the previous stage as a parental vector. The selected vector center can be calculated as follow:

$$X_{\text{mean}}^{g+1} = \frac{1}{\lambda} \sum_{i=1}^{\lambda} w_i Vpop_i^{\lambda_{\text{best}}} |w_i = \ln(\lambda + 1) \times \left( \sum_{j=1}^{\lambda} (\ln(\lambda + 1) - \ln(j)) \right), \tag{12}$$

where  $\lambda$  can be calculated as  $\lfloor \frac{N}{2} \rfloor$ ,  $i$  refers to the individual index,  $w_i$  refers to recombination weight. Here, two evolution paths can be computed to track the population mean changes with an exponential decay of the past.

$$p_{\sigma}^{g+1} = (1 - c_{\sigma})p_{\sigma}^g + \sqrt{c_{\sigma}(2 - c_{\sigma})\lambda_w} \frac{1}{\sigma^g} (c^g)^{-1/2} (X_{\text{mean}}^{g+1} - X_{\text{mean}}^g) \tag{13}$$

$$p_c^{g+1} = (1 - c_c)p_c^g + h_{\sigma} \sqrt{c_c(2 - c_c)\lambda_w} \frac{1}{\sigma^g} (X_{\text{mean}}^{g+1} - X_{\text{mean}}^g) \tag{14}$$

where  $\lambda_w^{-1} = \sum_{i=1}^{\lambda} w_i^2$ ,  $c_{\sigma} = (\lambda_w + 2)/(N + \lambda_w + 3)$ ,  $c_c = 4/(N + 4)$ ,  $h_{\sigma} = 1$  if  $\|p_{\sigma}^{g+1}\|$  is large.

**Step 3:** Updating the step size

$\sigma^{g+1}$  can be updated using Eq. (15).

$$\sigma^{g+1} = \sigma^g \times \exp \left( \frac{c_{\sigma}}{d_{\sigma}} \left( \frac{\|p_{\sigma}^{g+1}\|}{E|N(0, I)|} - 1 \right) \right) \tag{15}$$

Also, covariance matrix  $c^{g+1}$  is constructed using Eq. (16).

$$c^{g+1} = (1 - c_1 - c_{\lambda})c^g + c_1 p_c^{g+1} (p_c^{g+1})^T + c_{\lambda} \sum_{i=1}^{\lambda} w_i \frac{Vpop_i^{\lambda_{\text{best}}} - X_{\text{mean}}^g}{\sigma^g} \cdot \frac{(Vpop_i^{\lambda_{\text{best}}} - X_{\text{mean}}^g)^T}{\sigma^g} \tag{16}$$

where  $c_1, c_2$  have

$$d_{\sigma} = 1 + c_{\sigma} + 2 \max \{0, (\sqrt{\lambda_w} - 1/\sqrt{N + 1}) - 1\} \tag{17}$$

$$c_1 = \frac{1}{\lambda_w} \left( \left( 1 - \frac{1}{\lambda_w} \right) \min \left\{ 1, \frac{2\lambda_w - 1}{(N + 2)^2 + \lambda_w} + \lambda_w \right\} + \frac{1}{\lambda_w} \cdot \frac{2}{\lambda_w} (N + \sqrt{2})^2 \right) \tag{18}$$

$$C_{\lambda} = (\lambda_w - 1)C_1 \tag{19}$$

### 3.3 Immune response

According to the host cell immune influence system, only the highest performance virus will retain its properties to the next generation and the others are killed by the immune system. Hence, following steps are used to model the virus evolution.

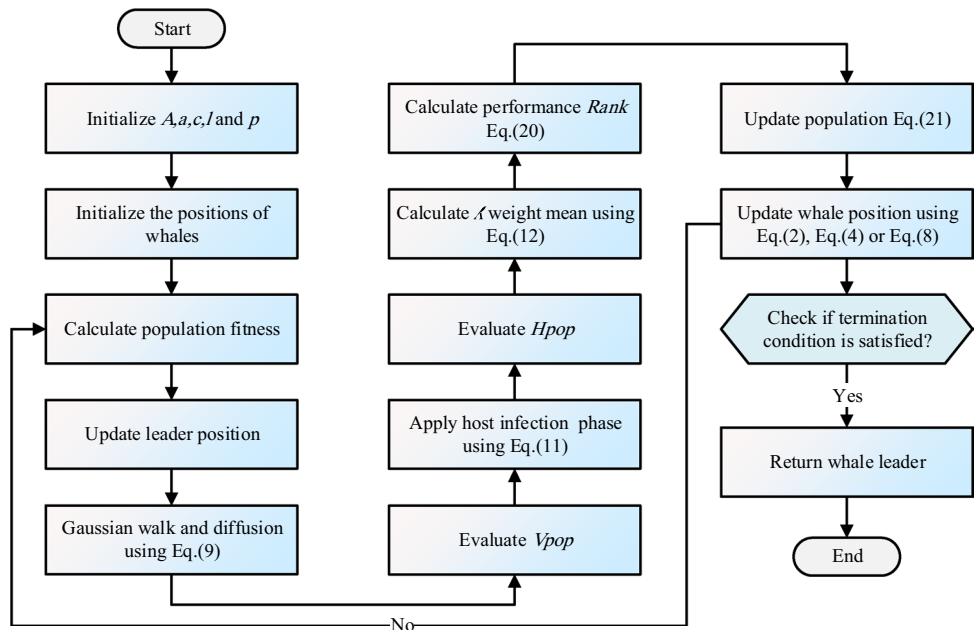
**Step 1:** Performance rank evaluation

$Pr_{rank(1)}$  can be calculated as follow.

$$Pr_{rank(1)} = \frac{(N - i + 1)}{N} \tag{20}$$

**Step 2:** Evolution of individuals

**Fig. 1** The flowchart of the proposed method



$$\begin{cases} Vpop_{i,j} = Vpop_{k,j} - rand \times \\ (Vpop_{h,j} - Vpop_{i,j}) & r > Pr_{rank(i)} \\ Vpop_{i,j} = Vpop_{i,j} & \text{otherwise} \end{cases} \quad (21)$$

where the 3 variables  $k, i, h$  are chosen randomly from  $[1, 2, 3, \dots, N]$  such that  $i \neq k \neq h$ , and  $j \in [1, 2, 3, \dots, d]$  and  $rand$  and  $r$  are the random values  $\in [0, 1]$ .

## 4 Proposed algorithm

In this section, the structure of the proposed WOA-based method is explained in detail, as given in Fig. 1. The basic WOA has some core limitations, especially in solving complex problems, mainly the multimodal functions and high dimensional ones. The main WOA's limitations are dropping into local optima and the problem of the slow convergence.

VCSWOA aims to overcome these limitations by revisiting the WOA based on the core components of Gaussian walk,

CMA-ES, and evolution strategy that appeared in the VCS. These ideas are to enhance the convergence speed and local optima avoidance of the WOA method. Here, the components of the VCS algorithm are devoted to performing intensification drifts to make the WOA algorithm more capable of avoiding local optima, which will reflect an improvement in exploitation abilities. On the other hand, the conventional cores of the WOA are utilized to handle exploratory patterns we need during a well-organized searching around the regions of the feature domain. In this way, we can reach a well-harmonized balance between exploitation and exploration procedures.

The pseudo-code of VCSWOA is shown in Algorithm , and it works as follows: An initial whale population is generated randomly at the initial state. Then, the three phases of Gaussian walk, CMA-ES, and evolution strategy are performed to further evolve the immature population: i.e., viruses diffusion, host cell infection, and immune response in VCS. After that, the updating phase of each search agent's position is done based on  $p$  and  $|A|$  values.

**Table 1** CEC2017 benchmark functions

No.	Types	Name	Opt	
F1	Unimodal	Shifted and rotated bent cigar function	100	
F2		Shifted and rotated sum of different power function	200	
F3	Multimodal	Shifted and rotated Zakharov function	300	
F4		Shifted and rotated Rosenbrock's function	400	
F5		Shifted and rotated Rastrigin's function	500	
F6		Shifted and rotated expanded Scaffer's F6 function	600	
F7		Shifted and rotated Lunacek bi-Rastrigin function	700	
F8		Shifted and rotated non-continuous Rastrigin's function	800	
F9		Shifted and rotated Lévy function	900	
F10		Shifted and rotated Schwefel's function	1000	
F11		Hybrid	Hybrid function 1 ( $N = 3$ )	1100
F12			Hybrid function 2 ( $N = 3$ )	1200
F13	Hybrid function 3 ( $N = 3$ )		1300	
F14	Hybrid function 4 ( $N = 4$ )		1400	
F15	Hybrid function 5 ( $N = 4$ )		1500	
F16	Hybrid function 6 ( $N = 4$ )		1600	
F17	Hybrid function 6 ( $N = 5$ )		1700	
F18	Hybrid function 6 ( $N = 5$ )		1800	
F19	Hybrid function 6 ( $N = 5$ )		1900	
F20	Hybrid function 6 ( $N = 6$ )		2000	
F21	Composition	Composition function 1 ( $N = 3$ )	2100	
F22		Composition function 2 ( $N = 3$ )	2200	
F23		Composition function 3 ( $N = 4$ )	2300	
F24		Composition function 4 ( $N = 4$ )	2400	
F25		Composition function 5 ( $N = 5$ )	2500	
F26		Composition function 6 ( $N = 5$ )	2600	
F27		Composition function 7 ( $N = 6$ )	2700	
F28		Composition function 8 ( $N = 6$ )	2800	
F29		Composition function 9 ( $N = 3$ )	2900	
F30		Composition function 10 ( $N = 3$ )	3000	



**Algorithm 2** VCSWOA

---

**Input:**  
Number of whales in the population ( $n$ )  
Maximum function evaluation number ( $MaxFEs$ )  
Number of dimensions ( $dim$ )  
selected best individuals number ( $\lambda = \lfloor \frac{N}{2} \rfloor$ )

**Output:**  
Optimal whale Position  
Positions=Initialize a the population of  $n$  whales  
Find  $X^*$  = best search agent threads  
EFs=0

**while**  $FEs < MaxFEs$  **do**  
  Check the boundary  
  Apply Gaussian random walk and diffusion phase Eq. (9)  
  FEs=FEs+N  
  Evaluate  $V_{pop}$   
  Host infection phase using Eq. (11)  
  FEs=FEs+N  
  Evaluate  $H_{pop}$   
  select  $\lambda$  best solution  
  calculate  $\lambda$  weight means using Eq. (15)  
  update population using Eq. (21)  
  **if** Best score < Leader score **then**  
    Leader pos=Best pos  
    Leader score=Best score  
  **end if**  
  **for**  $whale_i$  belong to whales **do**  
    Calculate and Update  $a, A, C, p$  and  $l$   
    FEs=FEs+1  
    **if**  $p < 0.5$  **then**  
      **if** ( $|A| < 1$ ) **then**  
        Update position by Eq. (2)  
      **else** ( $|A| \geq 1$ )  
        Select a random search agent ( $X_{rand}$ )  
      **end if**  
    **else** ( $p \geq 0.5$ )  
      Update position by Eq. (4)  
    **end if**  
    Update  $\mathbf{X}(t+1)$  from Eq. (5)  
  **end for**  
  Check if any search agent goes beyond the search space  
  Calculate the fitness of each search agent  
  Update  $X^*$  if there is a better solution  
  t=t+1  
**end while**

---

## 5 Experiment

In this section, many experiments have been performed to prove the efficiency of the proposed algorithm: benchmark functions, Engineering problems, and image segmentation problems.

### 5.1 Benchmark functions

Thirty functions from the IEEE CEC2017 benchmark have been used. Table 1 defines these functions and their type including unimodal, multimodal, hybrid, and composite. VCSWOA has been compared with other eight WOA variants namely: chaotic WOA (CWOA) [81], Opposition

learning-based WOA (OBWOA) [82], A-C parametric WOA (ACWOA) [83], Enhanced associative learning-based exploratory WOA (BMWOA), improved WOA (IWOA) [84], Balanced WOA with levy flight and chaotic local search (BWOA) [60], Multi-strategy boosted mutative WOA (CCMWOA) [], and Levy flight-based WOA (LWOA) [57]. The parameter settings for each algorithm are given in Table 2. The number of individuals, number of dimensions, and the maximum number of function evaluations ( $MaxFEs$ ) are given in Table 3. We used same conditions as per fair comparisons settings in artificial intelligence community [85, 86].

Table 4 shows the experiment results in terms of average (mean), standard deviation (std), best (min), and worst

**Table 2** The parameter settings for the algorithms

Algorithm	Parameters
CWOA	$cindex = 5; a_1 = [0, 2]; a_2 = [-2, -1]; A = [-a_1, a_1]; C = [0, 2]; b = 1; l = [1, a_2]; p = [0, 1]$
OBWOA	$a_1 \in [0, 2]; a_2 \in [-2, -1]; A \in [-a_1, a_1]; C \in [0, 2]; b = 1; l \in [1, a_2]; p \in [0, 1]$
ACWOA	$w \in [0.5, 1]; a_1 \in [0, 2]; a_2 \in [-2, -1]; A \in [-a_1, a_1]; C \in [0, 2]; b = 1; l \in [1, a_2]; p \in [0, 1]$
BMWOA	$bw = 0.001; beta = 0.1; a_1 \in [0, 2]; a_2 \in [-2, -1]; A \in [-a_1, a_1]; C \in [0, 2]; b = 1; l \in [1, a_2]; p \in [0, 1]$
IWOA	$CR = 0.9; a_1 \in [0, 2]; a_2 \in [-2, -1]; A \in [-a_1, a_1]; C \in [0, 2]; b = 1; l \in [1, a_2]; p \in [0, 1]$
BWOA	$m = 2500; a_1 \in [0, 2]; a_2 \in [-2, -1]; A \in [-a_1, a_1]; C \in [0, 2]; b = 1; l \in [1, a_2]; p \in [0, 1]$
CCMWOA	$m = 1500; setCan \in [0, 1]; a_1 \in [0, 2]; a_2 \in [-2, -1]; A \in [-a_1, a_1]; C \in [0, 2]; b = 1; l \in [1, a_2]; p \in [0, 1]$
LWOA	$S \in [lb, ub], s = [0, S]; a_1 \in [0, 2]; a_2 \in [-2, -1]; A \in [-a_1, a_1]; C \in [0, 2]; b = 1; l \in [1, a_2]; p \in [0, 1]$

(max). From this table, it can be noticed that VCSWOA ranked first in all unimodal functions (F1–F3) in Avg and Std values. However, in multimodal ones, VCSWOA has ranked first in avg at five functions (F4, F6, F8, F9, and F10), and ranked second in the other 3 functions. For both composite and hybrid functions, VCSWOA achieved the highest value in 7 functions and the second highest in other 8 functions. Also, Table 5 shows the Wilcoxon signed-rank [87] results in which VCSWOA has considered superior compared with other algorithms with a  $p$  value smaller than 5%. Figure 2 shows the convergence curve for 10 selected functions.

### 5.2 Engineering problems

In this subsection, four different engineering problems have been used: pressure vessel design problem, welded beam design problem, tension/compression spring design problem, and cantilever beam design problem.

#### 5.2.1 Pressure vessel design problem

Pressure vessel design problem is considered as a one of the wide engineering design problems which aims to find the lowest materials cost of the pressure vehicle. It's consist of 4 parameters(Shell thickness  $T_s$ , Cylindrical length  $L$ , head

**Table 3** The parameter settings

No.	Parameter name	Value
1	Population size	30
2	No of dim	30
3	MaxFEs	dim*10,000

thickness  $T_k$  and Radius  $R$ ). The mathematical design can be formulated as:

**Minimize:**  $f(x) = 0.6224x_1x_3x_4 + 1.7781x_2x_3^2 + 3.1661x_1^2x_4 + 19.84x_1^2x_3$   
**Subject to:**  $g_1(x) = -x_1 + 0.0193x$   
 $g_2(x) = -x_2 + 0/00954x_3 \leq 0$   
 $g_3(x) = -\pi x_3^2x_4 - (4/3)\pi x_3^3 + 1,296,000 \leq 0$

$g_4(x) = x_4 - 240 \leq 0$   
**Variable Range**  $0 \leq x_i \leq 100, \quad i = 1, 2$   
 $0 \leq x_i \leq 200, \quad i = 3, 4$

Table 6 shows the results of VCSWOA compared with SMA, WOA, GWO, MFO, ACO, HPSO, and BA. It's obvious that the proposed algorithm has less cost.

#### 5.2.2 Welded beam design problem

This problem has 4 parameters: bar length( $l$ ), bar height( $t$ ), Thickness of welded( $h$ ), and thickness of bar( $b$ ). Its mathematical equations can be shown as below:

**Minimize:**  
 $f_1(x) = 1.10471 * x(1)^2 * x(2) + 0.04811 * x(3) * x(4) * (14.0 + x(2))$

**Subject to:**  
 $g_1(x) = \tau - 13,600$   
 $g_2(x) = \sigma - 30,000$   
 $g_3(x) = x(1) - x(4)$   
 $g_4(x) = 6000 - p$

**Variable Range**  
 $0.125 \leq x_1 \leq 5$   
 $0.1 \leq x_2 \leq 10$   
 $0.1 \leq x_3 \leq 10$   
 $0.125 \leq x_4 \leq 5$

The results in Table 7 shows that VCSWOA has reach the most near optimal solution against many metaheuristic algorithms.

#### 5.2.3 Tension/compression spring design problem

The third problem used is Tension/Compression Spring problem which has 3 parameters :coil diameter( $D$ ), wire diameter( $d$ ), and number of active soils( $N$ ). The mathematical formulation is shown below:

**Minimize:**  
 $f(x) = (x_3 + 2)x_2x_1^2$   
**Subject to:**  
 $g_1(x) = 1 - (x_2^3x_3/71,785x_1^4) \leq 0$



**Table 4** The comparison results of all algorithms over 30 functions

	F1				F2			
	Avg	Std	Min	Max	Avg	Std	Min	Max
VCSWOA	<b>3.05E+03</b>	<b>4.94E+03</b>	<b>2.57E+02</b>	<b>2.01E+04</b>	<b>4.12E+05</b>	<b>1.75E+06</b>	<b>2.00E+02</b>	<b>9.52E+06</b>
CWOA	3.37E+09	2.91E+09	6.02E+07	1.32E+10	4.02E+31	1.09E+32	2.65E+19	5.12E+32
OBWOA	4.41E+07	3.44E+07	8.56E+06	1.25E+08	2.75E+24	8.49E+24	7.17E+17	4.17E+25
ACWOA	5.10E+09	2.20E+09	2.01E+09	1.02E+10	4.47E+34	2.25E+35	1.86E+22	1.23E+36
BMWOA	2.29E+08	1.11E+08	6.01E+07	5.35E+08	1.88E+24	7.42E+24	1.63E+18	3.88E+25
IWOA	1.88E+06	1.83E+06	2.20E+05	7.13E+06	6.23E+19	3.16E+20	1.51E+13	1.73E+21
BWOA	1.78E+08	9.60E+07	4.78E+07	4.59E+08	1.07E+27	5.81E+27	2.74E+18	3.19E+28
CCMWOA	1.87E+10	5.73E+09	6.95E+09	3.16E+10	8.21E+38	3.01E+39	1.43E+25	1.54E+40
LWOA	4.93E+05	1.24E+05	3.32E+05	8.56E+05	4.33E+06	2.27E+07	1.08E+03	1.24E+08
	F3				F4			
	Avg	Std	Min	Max	Avg	Std	Min	Max
VCSWOA	<b>3.11E+02</b>	<b>7.18E+00</b>	<b>3.03E+02</b>	<b>3.29E+02</b>	<b>4.93E+02</b>	2.65E+01	4.23E+02	<b>5.44E+02</b>
CWOA	1.57E+05	4.61E+04	8.07E+04	2.60E+05	7.00E+02	1.90E+02	5.27E+02	1.41E+03
OBWOA	5.41E+04	1.87E+04	3.82E+04	1.43E+05	5.63E+02	4.40E+01	4.95E+02	6.94E+02
ACWOA	4.98E+04	1.28E+04	3.90E+04	8.17E+04	1.23E+03	6.22E+02	6.64E+02	4.24E+03
BMWOA	7.17E+04	9.13E+03	4.98E+04	8.45E+04	6.13E+02	4.17E+01	5.42E+02	7.15E+02
IWOA	8.44E+04	3.18E+04	3.89E+04	1.49E+05	5.30E+02	4.24E+01	<b>4.10E+02</b>	6.38E+02
BWOA	5.85E+04	1.15E+04	3.70E+04	8.60E+04	6.00E+02	4.83E+01	5.38E+02	7.44E+02
CCMWOA	7.82E+04	4.33E+03	6.71E+04	8.70E+04	3.50E+03	1.13E+03	1.42E+03	5.91E+03
LWOA	5.14E+02	1.50E+02	3.64E+02	1.16E+03	4.99E+02	<b>2.18E+01</b>	4.67E+02	5.55E+02
	F5				F6			
	Avg	Std	Min	Max	Avg	Std	Min	Max
VCSWOA	7.65E+02	4.59E+01	6.37E+02	<b>8.29E+02</b>	<b>6.55E+02</b>	7.06E+00	6.41E+02	<b>6.70E+02</b>
CWOA	8.14E+02	5.99E+01	7.28E+02	1.01E+03	6.72E+02	9.69E+00	6.52E+02	6.87E+02
OBWOA	8.01E+02	3.21E+01	7.24E+02	8.44E+02	6.64E+02	6.66E+00	6.52E+02	6.76E+02
ACWOA	7.97E+02	3.35E+01	7.26E+02	8.56E+02	6.66E+02	<b>6.40E+00</b>	6.55E+02	6.79E+02
BMWOA	7.86E+02	4.95E+01	6.96E+02	8.79E+02	6.65E+02	9.27E+00	6.39E+02	6.78E+02
IWOA	<b>7.46E+02</b>	5.37E+01	<b>6.29E+02</b>	8.88E+02	<b>6.55E+02</b>	9.43E+00	<b>6.30E+02</b>	6.73E+02
BWOA	7.68E+02	<b>3.30E+01</b>	7.11E+02	8.17E+02	6.63E+02	7.21E+00	6.46E+02	6.74E+02
CCMWOA	8.33E+02	3.41E+01	7.22E+02	8.71E+02	6.74E+02	6.05E+00	6.65E+02	6.84E+02
LWOA	7.51E+02	5.35E+01	6.57E+02	8.76E+02	6.63E+02	1.11E+01	6.49E+02	6.96E+02
	F7				F8			
	Avg	Std	Min	Max	Avg	Std	Min	Max
VCSWOA	1.26E+03	<b>6.40E+01</b>	1.14E+03	1.36E+03	<b>9.69E+02</b>	2.62E+01	9.19E+02	<b>1.01E+03</b>
CWOA	1.26E+03	7.72E+01	1.09E+03	1.42E+03	1.02E+03	5.43E+01	9.31E+02	1.15E+03
OBWOA	1.28E+03	7.34E+01	1.06E+03	1.43E+03	1.02E+03	3.99E+01	9.65E+02	1.11E+03
ACWOA	1.25E+03	5.99E+01	1.08E+03	1.35E+03	1.01E+03	2.69E+01	9.72E+02	1.07E+03
BMWOA	1.25E+03	7.36E+01	1.11E+03	1.36E+03	1.01E+03	3.10E+01	9.49E+02	1.08E+03
IWOA	1.15E+03	8.53E+01	<b>9.42E+02</b>	<b>1.35E+03</b>	9.90E+02	4.39E+01	9.37E+02	1.12E+03
BWOA	1.26E+03	7.46E+01	1.07E+03	<b>1.35E+03</b>	9.77E+02	<b>2.19E+01</b>	9.30E+02	1.02E+03
CCMWOA	1.28E+03	7.24E+01	1.13E+03	1.40E+03	1.05E+03	2.94E+01	9.85E+02	1.10E+03
LWOA	<b>1.12E+03</b>	9.05E+01	9.80E+02	<b>1.35E+03</b>	1.01E+03	5.87E+01	<b>9.12E+02</b>	1.17E+03

**Table 4** (continued)

	F9				F10			
	Avg	Std	Min	Max	Avg	Std	Min	Max
VCSWOA	<b>5.33E+03</b>	<b>4.40E+02</b>	4.31E+03	<b>6.22E+03</b>	<b>4.81E+03</b>	6.57E+02	3.72E+03	<b>6.59E+03</b>
CWOA	9.41E+03	3.82E+03	4.80E+03	1.83E+04	6.44E+03	7.92E+02	4.92E+03	7.83E+03
OBWOA	7.06E+03	9.82E+02	5.05E+03	8.94E+03	6.26E+03	6.46E+02	4.66E+03	7.84E+03
ACWOA	7.36E+03	9.72E+02	5.68E+03	9.65E+03	6.84E+03	9.43E+02	4.94E+03	8.57E+03
BMWOA	7.73E+03	1.08E+03	4.98E+03	9.97E+03	7.37E+03	<b>5.99E+02</b>	5.85E+03	8.24E+03
IWOA	7.03E+03	2.35E+03	4.01E+03	1.33E+04	5.73E+03	7.03E+02	4.21E+03	7.07E+03
BWOA	6.25E+03	8.00E+02	4.77E+03	7.88E+03	6.33E+03	8.37E+02	4.61E+03	7.84E+03
CCMWOA	7.77E+03	1.24E+03	4.91E+03	1.05E+04	7.30E+03	6.07E+02	6.52E+03	8.81E+03
LWOA	6.64E+03	1.75E+03	<b>3.52E+03</b>	1.24E+04	5.25E+03	8.54E+02	<b>3.32E+03</b>	7.29E+03
	F11				F12			
	Avg	Std	Min	Max	Avg	Std	Min	Max
VCSWOA	<b>1.20E+03</b>	<b>3.51E+01</b>	1.14E+03	<b>1.27E+03</b>	<b>2.77E+06</b>	<b>1.50E+06</b>	<b>2.60E+05</b>	<b>6.63E+06</b>
CWOA	3.29E+03	1.12E+03	1.47E+03	5.41E+03	1.02E+08	1.11E+08	1.45E+07	4.60E+08
OBWOA	1.70E+03	2.85E+02	1.37E+03	2.86E+03	5.32E+07	3.33E+07	1.35E+07	1.30E+08
ACWOA	2.76E+03	6.67E+02	1.81E+03	4.29E+03	5.01E+08	3.26E+08	9.16E+07	1.51E+09
BMWOA	1.70E+03	1.76E+02	1.37E+03	2.13E+03	7.54E+07	4.72E+07	7.58E+06	1.98E+08
IWOA	1.36E+03	1.10E+02	1.23E+03	1.85E+03	7.74E+06	6.35E+06	1.69E+06	2.59E+07
BWOA	1.82E+03	2.42E+02	1.51E+03	2.67E+03	1.17E+08	9.68E+07	1.30E+07	3.65E+08
CCMWOA	3.39E+03	8.42E+02	1.83E+03	6.36E+03	2.62E+09	1.72E+09	4.83E+08	6.35E+09
LWOA	1.28E+03	5.82E+01	<b>1.13E+03</b>	1.38E+03	4.02E+06	2.38E+06	7.13E+05	1.06E+07
	F13				F14			
	Avg	Std	Min	Max	Avg	Std	Min	Max
VCSWOA	4.20E+04	2.22E+04	<b>9.34E+03</b>	<b>9.82E+04</b>	<b>2.24E+04</b>	<b>1.41E+04</b>	3.30E+03	<b>5.49E+04</b>
CWOA	1.20E+05	7.45E+04	2.59E+04	3.25E+05	1.33E+06	1.15E+06	5.74E+04	4.89E+06
OBWOA	2.88E+05	1.29E+05	1.01E+05	5.78E+05	7.32E+05	7.33E+05	2.86E+04	2.68E+06
ACWOA	1.69E+08	5.14E+08	6.59E+06	2.06E+09	1.30E+06	8.25E+05	5.85E+04	2.86E+06
BMWOA	4.16E+05	5.36E+05	6.07E+04	2.71E+06	7.32E+05	7.08E+05	1.48E+04	3.16E+06
IWOA	<b>2.58E+04</b>	<b>1.78E+04</b>	9.79E+03	9.21E+04	6.28E+05	5.59E+05	2.50E+04	1.79E+06
BWOA	2.16E+05	1.01E+05	7.65E+04	4.60E+05	1.39E+06	1.21E+06	2.69E+04	4.48E+06
CCMWOA	6.86E+07	7.81E+07	6.40E+06	4.25E+08	1.43E+06	1.21E+06	4.56E+04	4.27E+06
LWOA	1.73E+05	1.01E+05	5.16E+04	5.02E+05	2.39E+04	1.70E+04	<b>2.12E+03</b>	8.18E+04
	F15				F16			
	Avg	Std	Min	Max	Avg	Std	Min	Max
VCSWOA	1.88E+04	<b>1.08E+04</b>	5.11E+03	5.26E+04	<b>2.85E+03</b>	3.79E+02	<b>2.08E+03</b>	3.64E+03
CWOA	2.44E+06	8.22E+06	3.64E+04	4.38E+07	3.60E+03	<b>3.70E+02</b>	2.99E+03	4.41E+03
OBWOA	7.75E+05	1.44E+06	2.82E+04	5.96E+06	3.58E+03	4.74E+02	2.70E+03	4.72E+03
ACWOA	6.41E+06	6.14E+06	7.01E+05	3.17E+07	3.90E+03	4.01E+02	3.01E+03	4.53E+03
BMWOA	9.00E+04	7.84E+04	1.37E+04	4.23E+05	3.44E+03	4.52E+02	2.63E+03	4.57E+03
IWOA	<b>1.61E+04</b>	1.12E+04	<b>3.97E+03</b>	<b>4.27E+04</b>	3.05E+03	3.40E+02	2.34E+03	<b>3.61E+03</b>
BWOA	1.62E+05	2.45E+05	1.90E+04	1.33E+06	3.74E+03	5.07E+02	2.66E+03	4.43E+03
CCMWOA	4.00E+06	5.21E+06	5.04E+04	2.08E+07	3.82E+03	5.09E+02	3.10E+03	4.92E+03
LWOA	6.89E+04	5.00E+04	1.82E+04	2.12E+05	2.96E+03	3.92E+02	2.41E+03	4.19E+03

**Table 4** (continued)

	F17				F18			
	Avg	Std	Min	Max	Avg	Std	Min	Max
VCSWOA	<b>2.46E+03</b>	2.62E+02	1.97E+03	<b>2.97E+03</b>	2.10E+05	2.06E+05	<b>3.23E+04</b>	1.13E+06
CWOA	2.65E+03	2.91E+02	2.08E+03	3.28E+03	6.35E+06	5.16E+06	6.94E+04	1.75E+07
OBWOA	2.54E+03	2.42E+02	2.15E+03	3.11E+03	7.46E+05	6.46E+05	8.64E+04	2.92E+06
ACWOA	2.49E+03	2.70E+02	2.02E+03	3.03E+03	2.55E+06	3.23E+06	2.17E+05	1.68E+07
BMWOA	2.46E+03	<b>2.29E+02</b>	1.98E+03	3.10E+03	4.31E+06	5.27E+06	1.58E+05	2.58E+07
IWOA	2.43E+03	2.69E+02	1.97E+03	3.06E+03	<b>2.05E+06</b>	2.32E+06	2.03E+05	9.21E+06
BWOA	2.67E+03	2.85E+02	2.09E+03	3.33E+03	2.35E+06	2.68E+06	9.97E+04	1.15E+07
CCMWOA	2.69E+03	2.63E+02	2.15E+03	3.29E+03	1.14E+07	1.69E+07	2.33E+05	7.78E+07
LWOA	<b>2.46E+03</b>	2.57E+02	<b>1.91E+03</b>	<b>2.97E+03</b>	2.60E+05	<b>1.25E+05</b>	8.92E+04	<b>6.24E+05</b>
	F19				F20			
	Avg	Std	Min	Max	Avg	Std	Min	Max
VCSWOA	<b>1.06E+04</b>	<b>1.06E+04</b>	<b>2.09E+03</b>	<b>5.70E+04</b>	<b>2.54E+03</b>	1.82E+02	2.27E+03	<b>2.92E+03</b>
CWOA	3.31E+06	6.99E+06	9.49E+04	3.90E+07	2.78E+03	2.22E+02	2.37E+03	3.22E+03
OBWOA	2.23E+06	1.79E+06	3.22E+04	6.50E+06	2.69E+03	1.84E+02	<b>2.22E+03</b>	3.02E+03
ACWOA	1.11E+07	2.14E+07	1.63E+06	1.21E+08	2.66E+03	<b>1.53E+02</b>	2.39E+03	2.99E+03
BMWOA	6.50E+05	7.40E+05	1.27E+04	3.54E+06	2.74E+03	2.19E+02	2.31E+03	3.15E+03
IWOA	1.27E+04	1.52E+04	2.23E+03	7.85E+04	2.58E+03	1.74E+02	2.32E+03	3.04E+03
BWOA	4.07E+06	4.11E+06	1.16E+05	1.58E+07	2.71E+03	2.07E+02	2.34E+03	3.08E+03
CCMWOA	3.94E+06	4.54E+06	3.92E+05	1.87E+07	2.71E+03	1.71E+02	2.40E+03	3.02E+03
LWOA	2.31E+05	1.17E+05	4.48E+04	5.36E+05	2.71E+03	2.30E+02	2.27E+03	3.08E+03
	F21				F22			
	Avg	Std	Min	Max	Avg	Std	Min	Max
VCSWOA	<b>2.53E+03</b>	4.29E+01	2.44E+03	2.64E+03	6.35E+03	2.03E+03	<b>2.30E+03</b>	<b>8.41E+03</b>
CWOA	2.61E+03	5.48E+01	2.52E+03	2.74E+03	7.17E+03	1.89E+03	2.57E+03	9.57E+03
OBWOA	2.57E+03	6.01E+01	2.44E+03	2.68E+03	6.26E+03	2.39E+03	2.62E+03	9.23E+03
ACWOA	2.58E+03	<b>4.24E+01</b>	2.49E+03	2.71E+03	4.87E+03	2.17E+03	2.77E+03	9.15E+03
BMWOA	2.53E+03	4.73E+01	2.43E+03	2.60E+03	<b>4.83E+03</b>	3.11E+03	2.39E+03	9.99E+03
IWOA	2.54E+03	5.09E+01	2.45E+03	2.65E+03	5.93E+03	2.25E+03	2.31E+03	8.47E+03
BWOA	2.57E+03	7.57E+01	<b>2.24E+03</b>	2.67E+03	6.59E+03	2.01E+03	2.34E+03	9.37E+03
CCMWOA	2.64E+03	4.58E+01	2.58E+03	2.75E+03	7.79E+03	1.26E+03	4.58E+03	9.85E+03
LWOA	2.53E+03	4.43E+01	2.45E+03	<b>2.62E+03</b>	6.93E+03	<b>1.16E+03</b>	2.31E+03	8.56E+03
	F23				F24			
	Avg	Std	Min	Max	Avg	Std	Min	Max
VCSWOA	<b>2.97E+03</b>	9.02E+01	<b>2.80E+03</b>	3.21E+03	<b>3.11E+03</b>	8.03E+01	<b>2.95E+03</b>	3.32E+03
CWOA	3.09E+03	8.76E+01	2.92E+03	3.26E+03	3.22E+03	1.10E+02	3.03E+03	3.44E+03
OBWOA	3.07E+03	1.11E+02	2.87E+03	3.28E+03	3.13E+03	9.43E+01	<b>2.95E+03</b>	3.34E+03
ACWOA	3.06E+03	7.47E+01	2.90E+03	3.24E+03	3.19E+03	7.18E+01	3.07E+03	3.35E+03
BMWOA	2.98E+03	<b>6.15E+01</b>	2.86E+03	3.12E+03	3.08E+03	<b>6.56E+01</b>	<b>2.95E+03</b>	<b>3.22E+03</b>
IWOA	3.01E+03	8.57E+01	2.83E+03	3.24E+03	3.15E+03	9.02E+01	2.96E+03	3.33E+03
BWOA	3.06E+03	1.00E+02	2.86E+03	3.26E+03	3.20E+03	1.03E+02	3.00E+03	3.42E+03
CCMWOA	3.20E+03	1.04E+02	3.02E+03	3.37E+03	3.32E+03	9.79E+01	3.09E+03	3.56E+03
LWOA	2.99E+03	6.36E+01	2.91E+03	<b>3.16E+03</b>	3.19E+03	1.05E+02	2.98E+03	3.39E+03

**Table 4** (continued)

	F25				F26			
	Avg	Std	Min	Max	Avg	Std	Min	Max
VCSWOA	2.91E+03	2.18E+01	<b>2.88E+03</b>	<b>2.95E+03</b>	7.23E+03	2.08E+03	<b>2.80E+03</b>	9.57E+03
CWOA	3.05E+03	8.44E+01	2.94E+03	3.42E+03	7.97E+03	1.02E+03	5.44E+03	9.55E+03
OBWOA	2.99E+03	4.11E+01	2.92E+03	3.13E+03	7.38E+03	1.27E+03	4.62E+03	9.50E+03
ACWOA	3.15E+03	1.10E+02	3.06E+03	3.48E+03	7.32E+03	1.07E+03	4.52E+03	<b>8.75E+03</b>
BMWOA	3.03E+03	4.64E+01	2.95E+03	3.14E+03	6.50E+03	1.54E+03	3.17E+03	8.81E+03
IWOA	2.93E+03	2.89E+01	2.89E+03	3.05E+03	7.13E+03	9.12E+02	5.37E+03	9.73E+03
BWOA	3.01E+03	4.95E+01	2.95E+03	3.10E+03	8.02E+03	1.12E+03	6.04E+03	1.02E+04
CCMWOA	3.35E+03	1.18E+02	3.12E+03	3.58E+03	8.86E+03	<b>8.31E+02</b>	6.62E+03	1.03E+04
LWOA	<b>2.90E+03</b>	<b>1.99E+01</b>	<b>2.88E+03</b>	<b>2.95E+03</b>	<b>6.28E+03</b>	1.26E+03	2.90E+03	7.64E+03
	F27				F28			
	Avg	Std	Min	Max	Avg	Std	Min	Max
VCSWOA	3.36E+03	7.04E+01	3.24E+03	3.55E+03	<b>3.20E+03</b>	3.45E+01	<b>3.10E+03</b>	<b>3.26E+03</b>
CWOA	3.40E+03	9.54E+01	3.28E+03	3.63E+03	3.50E+03	1.02E+02	3.30E+03	3.77E+03
OBWOA	3.40E+03	1.27E+02	3.24E+03	3.74E+03	3.37E+03	4.90E+01	3.30E+03	3.51E+03
ACWOA	3.46E+03	1.03E+02	3.26E+03	3.73E+03	3.70E+03	1.59E+02	3.48E+03	4.16E+03
BMWOA	3.34E+03	6.58E+01	3.23E+03	3.47E+03	3.41E+03	4.98E+01	3.34E+03	3.51E+03
IWOA	3.30E+03	7.80E+01	3.23E+03	3.65E+03	3.30E+03	2.63E+01	3.24E+03	3.37E+03
BWOA	3.39E+03	1.22E+02	3.27E+03	3.77E+03	3.40E+03	3.81E+01	3.33E+03	3.47E+03
CCMWOA	3.63E+03	2.03E+02	3.39E+03	4.37E+03	4.69E+03	3.86E+02	4.00E+03	5.56E+03
LWOA	<b>3.27E+03</b>	<b>4.04E+01</b>	<b>3.22E+03</b>	<b>3.38E+03</b>	3.23E+03	<b>2.46E+01</b>	3.19E+03	<b>3.26E+03</b>
	F29				F30			
	Avg	Std	Min	Max	Avg	Std	Min	Max
VCSWOA	4.34E+03	3.54E+02	<b>3.70E+03</b>	5.26E+03	<b>2.79E+05</b>	<b>2.73E+05</b>	<b>2.55E+04</b>	<b>1.05E+06</b>
CWOA	4.75E+03	3.69E+02	3.97E+03	5.86E+03	1.08E+07	8.12E+06	5.94E+05	2.99E+07
OBWOA	4.80E+03	4.25E+02	3.87E+03	5.56E+03	1.37E+07	8.53E+06	4.19E+06	4.59E+07
ACWOA	4.82E+03	3.71E+02	4.23E+03	5.65E+03	5.69E+07	4.15E+07	6.80E+06	1.53E+08
BMWOA	4.72E+03	3.68E+02	4.01E+03	5.59E+03	6.01E+06	4.00E+06	9.54E+05	2.02E+07
IWOA	<b>4.16E+03</b>	2.61E+02	3.66E+03	4.79E+03	6.12E+05	5.82E+05	1.58E+05	2.88E+06
BWOA	5.01E+03	4.38E+02	4.29E+03	5.84E+03	2.15E+07	1.55E+07	1.14E+06	5.25E+07
CCMWOA	5.36E+03	5.60E+02	4.32E+03	6.56E+03	5.91E+07	4.13E+07	3.35E+06	1.78E+08
LWOA	4.18E+03	<b>2.41E+02</b>	3.80E+03	<b>4.74E+03</b>	8.88E+05	3.82E+05	3.76E+05	2.32E+06

Bold are the best values

$$g_2(x) = (4x_2^2 - x_1x_2/12, 566(x_2x_1^3 - x_1^4) + (1/5108x_1^2)) - 10 \leq 0$$

$$g_3(x) = 1 - (140.45x_1/x_2^2x_3) \leq 0$$

$$g_4(x) = (x_2 + x_1)/1.5 - 1 \leq 0,$$

**Variable Range**

$$0.05 \leq x_1 \leq 2.00$$

$$0.25 \leq x_2 \leq 1.30$$

$$2.00 \leq x_3 \leq 15.00$$

The statistical results to this problem are shown in Table 8 in which the proposed algorithm is compared with GA, WOA, MVO, GSA, PSO and MFO and it's noticed that VCSWOA has the best result.

**5.2.4 Cantilever beam design problem**

The last engineering problem introduced in this subsection is the Cantilever beam design problem which consists of 5 square hollow cross-sections. It intends to dwindle the Cantilever beam mass. The problem formulation is shown as follows:

**Minimize:**

$$f(x) = 0.6224(x_1 + x_2 + x_3 + x_4 + x_5)$$

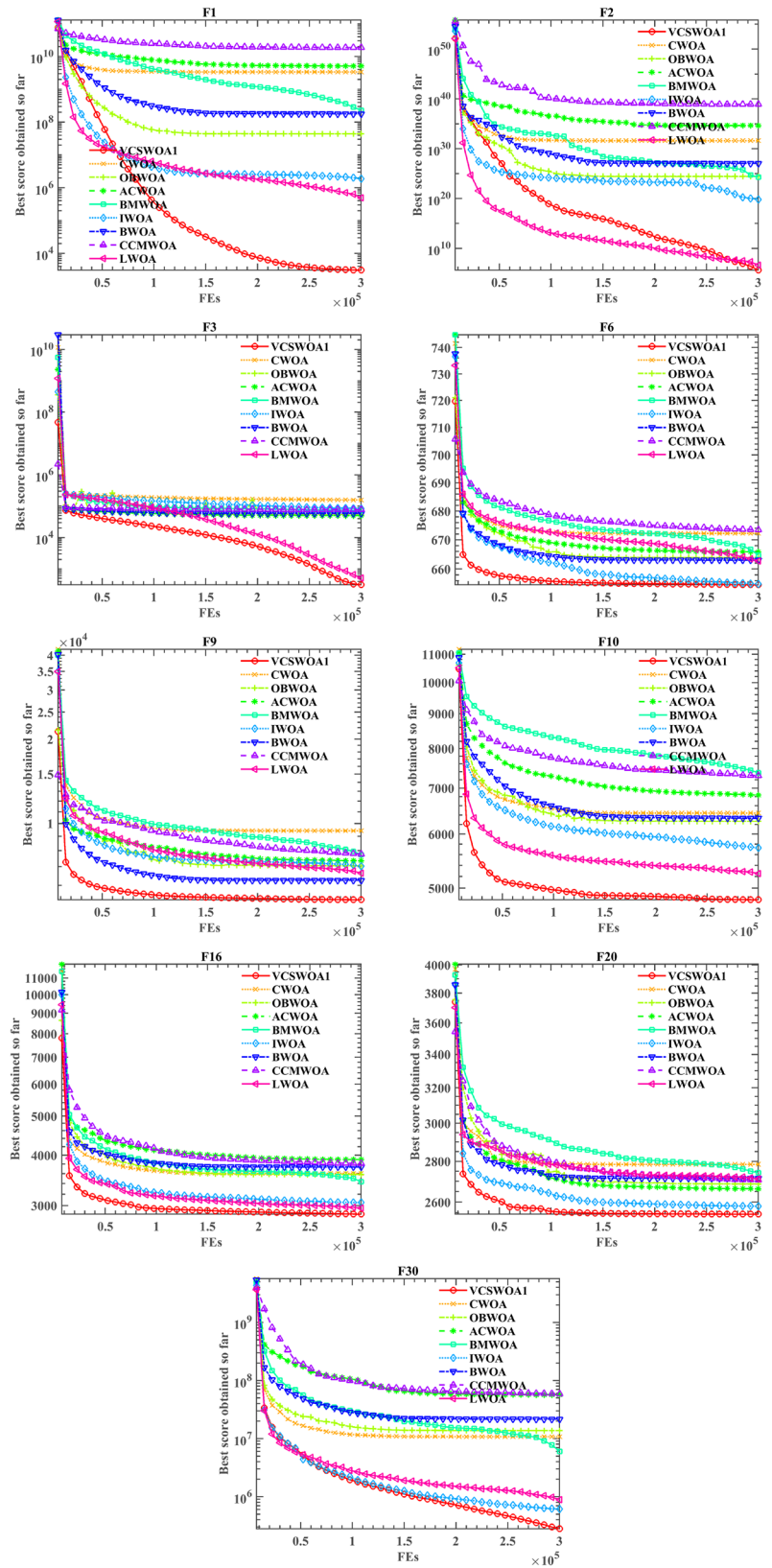
**Subject to:**

$$G(x) = 61/x_1^3 + 37/x_2^2 + 19/x_3^3 + 7/x_4 + 1/x_5^3$$

**Variable Range**

$$0.1 \leq x_i \leq 100, \quad i = 1, 2, 3, 4, 5$$

**Fig. 2** Unimodal and multi-modal functions convergence curve



**Table 5** The calculated  $p$  values from the signed-rank test

F.	CWOA	OBWOA	ACWOA	BMWOA	IWOA	BWOA	CCMWOA	LWOA
F1	1.73E-06	1.73E-06	1.73E-06	1.73E-06	1.73E-06	1.73E-06	1.73E-06	1.73E-06
F2	1.73E-06	1.73E-06	1.73E-06	1.73E-06	1.73E-06	1.73E-06	1.73E-06	5.45E-02
F3	1.73E-06	1.73E-06	1.73E-06	1.73E-06	1.73E-06	1.73E-06	1.73E-06	1.73E-06
F4	1.73E-06	1.73E-06	1.73E-06	1.73E-06	8.92E-05	1.73E-06	1.73E-06	3.93E-01
F5	1.48E-03	5.67E-03	5.67E-03	1.20E-01	1.71E-01	8.29E-01	1.13E-05	2.71E-01
F6	4.72E-06	1.36E-04	2.37E-05	1.06E-04	6.88E-01	1.15E-04	1.73E-06	2.96E-03
F7	0.95E-01	3.18E-01	2.29E-01	6.00E-01	4.29E-06	9.75E-01	4.05E-01	1.97E-05
F8	2.61E-04	6.98E-06	2.60E-05	4.90E-04	1.41E-01	2.54E-01	1.92E-06	1.66E-02
F9	5.75E-06	3.88E-06	1.92E-06	1.92E-06	1.04E-03	2.60E-05	2.13E-06	4.53E-04
F10	1.73E-06	6.98E-06	1.92E-06	1.73E-06	1.36E-04	1.02E-05	1.73E-06	5.45E-02
F11	1.73E-06	1.73E-06	1.73E-06	1.73E-06	1.73E-06	1.73E-06	1.73E-06	2.16E-05
F12	1.73E-06	1.73E-06	1.73E-06	1.73E-06	1.25E-04	1.73E-06	1.73E-06	5.45E-02
F13	9.31E-06	1.73E-06	1.73E-06	1.73E-06	1.59E-03	1.73E-06	1.73E-06	1.73E-06
F14	1.73E-06	2.13E-06	1.73E-06	1.92E-06	1.92E-06	1.73E-06	1.73E-06	6.73E-01
F15	1.73E-06	1.92E-06	1.73E-06	5.22E-06	1.20E-01	1.92E-06	1.73E-06	2.35E-06
F16	7.69E-06	1.97E-05	2.88E-06	1.36E-04	6.27E-02	3.88E-06	6.34E-06	5.30E-01
F17	2.41E-03	1.85E-01	6.73E-01	9.26E-01	7.50E-01	2.43E-02	4.11E-03	8.77E-01
F18	2.12E-06	1.89E-04	1.73E-06	1.73E-06	5.75E-06	6.98E-06	2.13E-06	4.28E-02
F19	1.73E-06	1.73E-06	1.73E-06	1.73E-06	5.86E-01	1.73E-06	1.73E-06	1.73E-06
F20	1.59E-03	1.85E-02	1.11E-02	5.29E-04	3.18E-01	6.04E-03	4.99E-03	4.39E-03
F21	2.84E-05	1.71E-03	1.49E-05	6.73E-01	2.71E-01	1.38E-03	2.35E-06	6.14E-01
F22	1.15E-01	8.13E-01	1.11E-02	5.19E-02	2.71E-01	7.19E-01	3.85E-03	2.62E-01
F23	1.05E-04	1.48E-03	6.16E-04	2.21E-01	2.18E-02	6.84E-03	4.29E-06	3.09E-01
F24	7.15E-04	1.85E-01	3.06E-04	1.59E-01	4.72E-02	1.48E-03	3.18E-06	5.67E-03
F25	1.73E-06	1.73E-06	1.73E-06	1.73E-06	4.90E-04	1.73E-06	1.73E-06	3.49E-01
F26	7.52E-02	8.29E-01	7.50E-01	6.27E-02	2.71E-01	3.18E-01	7.71E-04	3.33E-02
F27	1.58E-01	2.62E-01	1.60E-04	1.71E-01	1.48E-03	6.14E-01	2.60E-06	1.36E-05
F28	1.73E-06	1.73E-06	1.73E-06	1.73E-06	1.73E-06	1.73E-06	1.73E-06	6.16E-04
F29	1.60E-04	8.31E-04	4.20E-04	3.59E-04	3.87E-02	7.69E-06	2.35E-06	2.21E-01
F30	1.73E-06	1.73E-06	1.73E-06	1.73E-06	2.26E-03	1.73E-06	1.73E-06	1.13E-05

**Table 6** Optimization results for pressure vessel design problem

Algorithm	Optimization results			Cost	
	$T_s$	$T_h$	$R$	$L$	Cost
VCSWOA	0.87451	0.430244	45.24849	142.4528	5515.211
SMA [12]	0.8125	0.4375	42.09844	176.6366	6059.715
WOA [88]	0.812500	0.4375	42.0982	176.638	6059.7410
GWO [89]	0.8125	0.4345	42.0892	176.7587	6051.5639
MFO [90]	0.8125	0.4375	42.0984	176.6366	6059.7143
ACO [91]	0.8125	0.4375	42.1036	176.5727	6059.0888
HPSO [92]	0.8125	0.4375	42.0984	176.6366	6059.7143
BA [93]	0.8125	0.4375	42.0984	176.6366	6059.7143

Table 9 compares VCSWOA with many algorithms MFO, SOS, CS, MMA, and GCA. It is seen that VCSWOA achieved the best result. As per results, we can find the potential of the proposed WOA-based method is not limited

**Table 7** Optimization results for welded beam design problem

Algorithm	Optimization results				Cost
	$h$	$l$	$t$	$b$	
VCSWOA	0.18885	3.5685	9.025806	0.207104	1.72003
CSA	0.2054	3.2589	9.0384	0.2068	1.73604
WOA	0.205	3.4842	9.0374	0.2062	1.73049
MVO	0.2054	3.4731	9.0445	0.2056	1.72645
MFO	0.2057	3.4703	9.0364	0.2057	1.72452
SSA [94]	0.2057	3.4714	9.0366	0.2057	1.72491

to these cases and it can be applied to more complex cases such as image classification [95, 96].

### 5.3 Image segmentation

In literature, many techniques are existed to segment images such as Otsu [97], Kapur [98], etc which are used to divide



**Table 8** Optimization results for the Tension/compression design problem

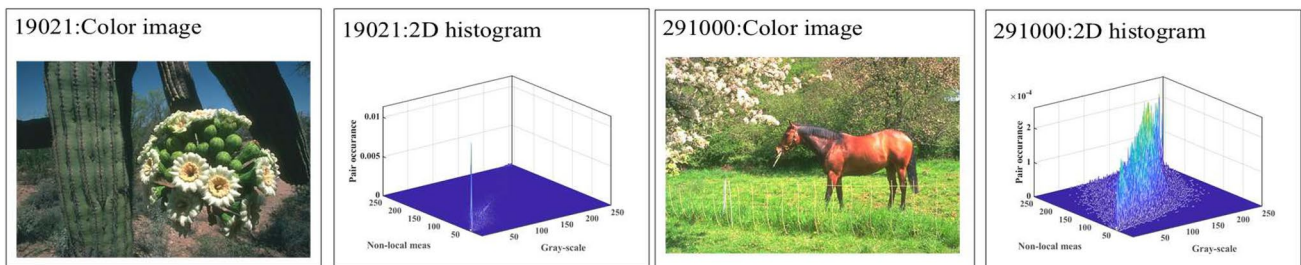
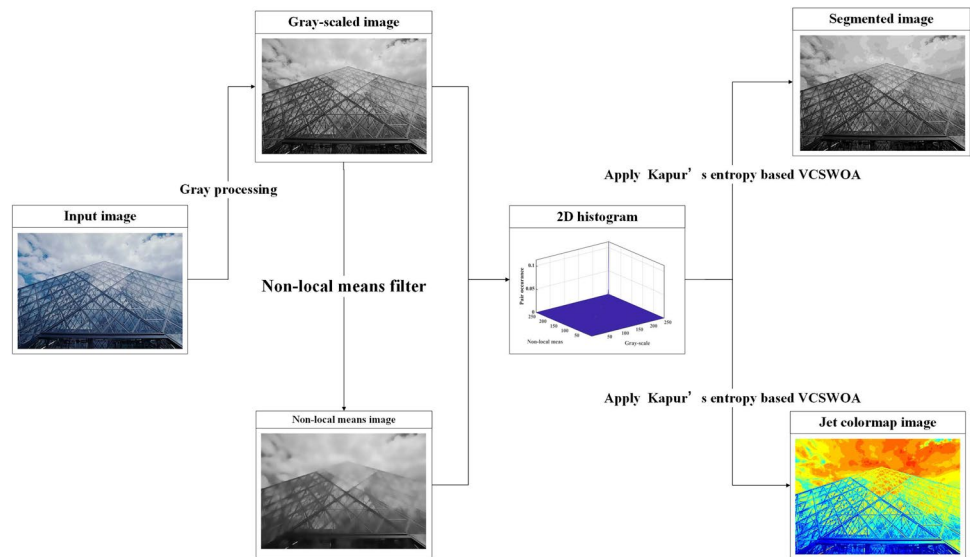
Algorithm	Optimization results			Cost
	$d$	$D$	$N$	
VCSWOA	0.05169	0.356736	11.28791	0.012665
GA	0.05010	0.31011	14.0000	0.013036
WOA	0.05120	0.34521	12.0040	0.012676
MVO	0.05251	0.37602	10.3351	0.012790
GSA	0.05027	0.32368	13.5254	0.012702
PSO	0.05000	0.31041	15.0000	0.013192
MFO	0.05000	0.31350	14.0327	0.012753

image histogram to different groups based on threshold values. Figure 3 shows the flowchart of Berkeley image segmentation(MIS) for 241,004. Here, to validate our algorithm VCSWOA, 8 images from BSDS500 are used namely: 291,000, 38,092, 86,068, 170,057, 61,060, 175,032, 223,061, and 19,021. Figure 4 shows these images and their 2D histogram. Different metaheuristic algorithms are used in order to compare their results with VCSWOA: WOA, BA, CS, CBA, SCA, BLP SO, IGWO, IWOA, and SCAD E. Finally, Peak Signal to Noise Ratio (PSNR) [99], Structural Similarity Index (SSIM) [100], and Feature Similarity Index (FSIM) [101] are used to evaluate image segmentation

**Table 9** Optimization results for cantilever beam problem

Algorithm	Optimization results					Cost
	$x_1$	$x_2$	$x_3$	$x_4$	$x_5$	
VCSWOA	6.015106	5.307156	4.499152	3.49513	2.157171	1.33996
MFO	5.9830	5.3167	4.4973	3.5136	2.1616	1.33998
SOS	6.0188	5.3034	4.4959	3.4990	2.1556	1.33996
CS	6.0089	5.3049	4.5023	3.5077	2.1504	1.33999
MMA	6.0100	5.3000	4.4900	3.4900	2.1500	1.3400
GCA	6.0100	5.3000	4.4900	3.4900	2.1500	1.3400

**Fig. 3** Flowchart of MIS for 241,004



**Fig. 4** Three-dimension view about 2D histograms of 19,021 and 291,000

**Table 10** The PSNR comparison results of VCSWOA and other methods

Image	Thres.	Item	VCSWOA	WOA	BA	CS	CBA	
291,000	2	AVG	<b>1.5469E+01</b>	1.4139E+01	1.3897E+01	1.4769E+01	1.4254E+01	
		STD	1.4761E+00	2.1959E+00	2.4638E+00	1.8668E+00	1.7854E+00	
	4	AVG	1.7513E+01	1.7192E+01	1.7589E+01	1.7643E+01	1.7404E+01	
		STD	1.2496E+00	1.9756E+00	1.2213E+00	1.4215E+00	1.6360E+00	
	6	AVG	<b>2.0709E+01</b>	2.0247E+01	1.9773E+01	2.0307E+01	2.0642E+01	
		STD	9.5755E−01	1.6762E+00	2.1459E+00	1.3320E+00	1.6209E+00	
	12	AVG	<b>2.6933E+01</b>	2.5977E+01	2.6811E+01	2.5762E+01	2.6791E+01	
		STD	<b>3.6690E−01</b>	1.0349E+00	5.0902E−01	9.7953E−01	6.7301E−01	
	16	AVG	<b>2.9321E+01</b>	2.8230E+01	2.8879E+01	2.8027E+01	2.8797E+01	
		STD	<b>3.4656E−01</b>	8.1473E−01	5.9989E−01	8.9664E−01	7.5941E−01	
	18	AVG	<b>3.0097E+01</b>	2.9088E+01	2.9594E+01	2.8607E+01	2.9684E+01	
		STD	<b>3.9234E−01</b>	7.2479E−01	1.0276E+00	1.1026E+00	8.7337E−01	
	38,092	2	AVG	1.5387E+01	1.5384E+01	1.5215E+01	1.5382E+01	1.5351E+01
			STD	4.3936E−02	3.8515E−02	1.2991E+00	4.7546E−02	7.4480E−01
		4	AVG	<b>2.0529E+01</b>	2.0395E+01	2.0206E+01	2.0125E+01	2.0273E+01
			STD	<b>2.0084E−01</b>	2.8220E−01	1.2453E+00	3.8400E−01	8.0005E−01
6		AVG	<b>2.3475E+01</b>	2.3283E+01	2.2896E+01	2.2677E+01	2.2158E+01	
		STD	<b>8.3431E−02</b>	4.2648E−01	8.7902E−01	6.1763E−01	2.3798E+00	
12		AVG	<b>2.6377E+01</b>	2.5152E+01	2.6043E+01	2.5512E+01	2.6331E+01	
		STD	<b>6.6003E−01</b>	7.9456E−01	2.6720E+00	7.1953E−01	8.0805E−01	
16		AVG	<b>2.9265E+01</b>	2.7852E+01	2.8393E+01	2.7846E+01	2.8177E+01	
		STD	<b>4.4913E−01</b>	8.9518E−01	1.2202E+00	9.0842E−01	9.9741E−01	
18		AVG	<b>3.0408E+01</b>	2.8551E+01	2.9355E+01	2.8475E+01	2.9228E+01	
		STD	<b>3.5656E−01</b>	1.0112E+00	1.0705E+00	1.0019E+00	1.4376E+00	
86,068		2	AVG	1.5408E+01	1.5386E+01	1.5121E+01	1.5403E+01	1.5401E+01
			STD	<b>7.2269E−15</b>	3.6534E−02	7.4762E−01	5.9756E−03	4.7379E−02
		4	AVG	<b>1.9891E+01</b>	1.9796E+01	1.8567E+01	1.9638E+01	1.9081E+01
			STD	<b>2.9325E−01</b>	2.9573E−01	2.5709E+00	3.3398E−01	7.2704E−01
	6	AVG	<b>2.1871E+01</b>	2.1561E+01	2.1677E+01	2.1716E+01	2.1774E+01	
		STD	<b>9.7778E−02</b>	3.6714E−01	1.0208E+00	2.9527E−01	2.4534E−01	
	12	AVG	<b>2.6344E+01</b>	2.3444E+01	2.6248E+01	2.3161E+01	2.5491E+01	
		STD	2.4088E+00	2.6082E+00	2.4976E+00	2.8482E+00	2.8115E+00	
	16	AVG	<b>2.9412E+01</b>	2.5078E+01	2.8657E+01	2.6035E+01	2.7680E+01	
		STD	<b>6.3045E−01</b>	2.9563E+00	2.2350E+00	2.3166E+00	3.2288E+00	
	18	AVG	<b>2.9456E+01</b>	2.6956E+01	2.8479E+01	2.6916E+01	2.7836E+01	
		STD	<b>1.2954E+00</b>	2.4324E+00	2.6393E+00	2.2689E+00	2.7271E+00	
	170,057	2	AVG	1.3852E+01	1.3751E+01	1.3791E+01	1.3603E+01	1.3921E+01
			STD	2.0594E−01	9.5548E−01	1.0196E+00	9.2202E−01	9.1945E−01
		4	AVG	1.8865E+01	1.8325E+01	1.8256E+01	<b>1.9270E+01</b>	1.8254E+01
			STD	<b>2.8104E−01</b>	1.3948E+00	1.5323E+00	7.7237E−01	1.5720E+00
6		AVG	<b>2.1849E+01</b>	2.1050E+01	2.1672E+01	2.1564E+01	2.1592E+01	
		STD	<b>7.6181E−01</b>	1.3121E+00	9.2326E−01	8.3760E−01	1.1731E+00	
12		AVG	<b>2.7977E+01</b>	2.6917E+01	2.6576E+01	2.6004E+01	2.6967E+01	
		STD	<b>7.0969E−01</b>	1.1501E+00	1.9470E+00	1.1942E+00	1.3415E+00	
16		AVG	<b>3.0352E+01</b>	2.9215E+01	2.8094E+01	2.7853E+01	2.9023E+01	
		STD	<b>5.3477E−01</b>	1.3431E+00	2.4247E+00	1.3126E+00	1.2279E+00	
18		AVG	<b>3.1418E+01</b>	2.9568E+01	2.9102E+01	2.8827E+01	2.9675E+01	
		STD	<b>5.3128E−01</b>	1.4872E+00	2.2030E+00	1.3816E+00	1.7367E+00	

**Table 10** (continued)

Image	Thres.	Item	VCSWOA	WOA	BA	CS	CBA
61,060	2	AVG	1.4356E+01	1.4049E+01	1.4032E+01	1.4234E+01	1.4139E+01
		STD	<b>1.1816E−01</b>	6.7220E−01	6.6207E−01	2.8012E−01	2.9366E−01
	4	AVG	1.8815E+01	1.8423E+01	1.8813E+01	1.8539E+01	<b>1.8862E+01</b>
		STD	<b>2.4711E−01</b>	8.3974E−01	7.6752E−01	3.6267E−01	3.4265E−01
	6	AVG	2.1473E+01	2.1380E+01	2.1197E+01	2.1126E+01	<b>2.1474E+01</b>
		STD	<b>3.3790E−01</b>	5.2729E−01	1.6500E+00	7.2119E−01	3.9212E−01
	12	AVG	<b>2.6133E+01</b>	2.5162E+01	2.5128E+01	2.5321E+01	2.5634E+01
		STD	<b>8.3500E−01</b>	1.3203E+00	2.2377E+00	1.1990E+00	1.5028E+00
	16	AVG	<b>2.8816E+01</b>	2.7887E+01	2.7648E+01	2.7137E+01	2.8255E+01
		STD	<b>1.0001E+00</b>	1.6246E+00	1.6622E+00	1.5419E+00	1.0464E+00
	18	AVG	<b>2.9906E+01</b>	2.8653E+01	2.8864E+01	2.8714E+01	2.8606E+01
		STD	1.1216E+00	1.2467E+00	1.6273E+00	<b>9.9666E−01</b>	1.2067E+00
175032	2	AVG	1.3812E+01	1.3835E+01	1.2815E+01	1.3847E+01	1.3253E+01
		STD	1.7202E−01	<b>1.4738E−02</b>	1.6036E+00	1.4902E−02	1.1813E+00
	4	AVG	1.8419E+01	1.8385E+01	1.8259E+01	1.8336E+01	1.8320E+01
		STD	<b>1.2114E−01</b>	1.7594E−01	8.2320E−01	1.7005E−01	8.0605E−01
	6	AVG	2.1213E+01	2.1003E+01	2.1209E+01	2.0931E+01	2.1055E+01
		STD	<b>1.6797E−01</b>	6.5009E−01	7.4971E−01	3.4788E−01	1.1952E+00
	12	AVG	<b>2.8808E+01</b>	2.7681E+01	2.6606E+01	2.6680E+01	2.7890E+01
		STD	<b>4.6737E−01</b>	1.2573E+00	3.1113E+00	9.7908E−01	8.5450E−01
	16	AVG	<b>3.1056E+01</b>	3.0001E+01	2.8702E+01	2.8608E+01	2.8856E+01
		STD	<b>6.8160E−01</b>	8.3821E−01	1.7951E+00	1.0730E+00	1.5784E+00
	18	AVG	<b>3.2171E+01</b>	2.9859E+01	2.8629E+01	2.9102E+01	2.9760E+01
		STD	<b>3.6441E−01</b>	1.8403E+00	2.6881E+00	1.9095E+00	2.4370E+00
223,061	2	AVG	<b>1.6721E+01</b>	1.5206E+01	1.5525E+01	1.5585E+01	1.6131E+01
		STD	4.2365E−01	2.2905E+00	2.1146E+00	2.8287E+00	8.8540E−01
	4	AVG	<b>2.0451E+01</b>	1.9366E+01	1.9038E+01	1.6999E+01	1.9424E+01
		STD	1.3275E+00	1.7030E+00	3.4719E+00	3.6009E+00	2.1386E+00
	6	AVG	<b>2.2436E+01</b>	1.9660E+01	2.0656E+01	1.9185E+01	2.0641E+01
		STD	2.3760E+00	3.7313E+00	3.0777E+00	3.6299E+00	3.5669E+00
	12	AVG	<b>2.7966E+01</b>	2.6284E+01	2.6744E+01	2.6247E+01	2.6837E+01
		STD	<b>1.8689E−01</b>	1.1467E+00	1.2547E+00	7.5128E−01	1.5959E+00
	16	AVG	<b>3.0086E+01</b>	2.8589E+01	2.8515E+01	2.8092E+01	2.8809E+01
		STD	<b>3.1224E−01</b>	9.1802E−01	2.0070E+00	8.3237E−01	1.1132E+00
	18	AVG	<b>3.1237E+01</b>	2.9520E+01	2.9461E+01	2.8892E+01	2.9660E+01
		STD	<b>1.2594E−01</b>	8.5945E−01	1.2496E+00	7.5785E−01	1.0214E+00
19,021	2	AVG	<b>1.6238E+01</b>	1.6036E+01	1.5678E+01	1.6014E+01	1.5379E+01
		STD	<b>9.9054E−02</b>	8.8069E−01	1.4377E+00	3.5023E−01	1.4737E+00
	4	AVG	<b>1.9356E+01</b>	1.9011E+01	1.9246E+01	1.8680E+01	1.9125E+01
		STD	5.7631E−01	4.8208E−01	6.4570E−01	<b>3.5639E−01</b>	9.8518E−01
	6	AVG	<b>2.2709E+01</b>	2.1677E+01	2.1817E+01	2.1411E+01	2.1857E+01
		STD	<b>2.4533E−01</b>	1.1769E+00	1.6717E+00	1.1426E+00	1.1902E+00
	12	AVG	2.6861E+01	2.6606E+01	2.6950E+01	2.6774E+01	<b>2.7311E+01</b>
		STD	<b>5.2986E−01</b>	1.1172E+00	1.1677E+00	6.7277E−01	8.2237E−01
	16	AVG	<b>2.9153E+01</b>	2.8754E+01	2.8813E+01	2.8531E+01	2.8813E+01
		STD	<b>5.3685E−01</b>	1.2670E+00	2.4828E+00	1.1967E+00	1.5402E+00
	18	AVG	3.0062E+01	2.9528E+01	2.9770E+01	2.9300E+01	<b>3.0362E+01</b>
		STD	<b>5.7887E−01</b>	1.3410E+00	1.7697E+00	1.0482E+00	9.2978E−01

Bold are the best values

**Table 11** The PSNR comparison results of VCSWOA and other methods

Image	Thres.	Item	VCSWOA	WOA	BA	CS	CBA
291,000	2	AVG	1.1540E+01	1.4249E+01	1.4272E+01	1.4199E+01	1.4009E+01
		STD	2.7555E+00	2.4146E-01	2.8738E-01	<b>2.0941E-01</b>	5.4376E-01
	4	AVG	1.5859E+01	1.8789E+01	<b>1.8579E+01</b>	1.7861E+01	1.6217E+01
		STD	1.8047E+00	<b>2.8304E-01</b>	3.4108E-01	9.0971E-01	1.2937E+00
	6	AVG	1.6921E+01	2.0607E+01	2.0686E+01	2.0446E+01	1.8123E+01
		STD	1.7870E+00	7.6795E-01	<b>7.2809E-01</b>	8.9592E-01	1.3799E+00
	12	AVG	2.2402E+01	2.4778E+01	2.4480E+01	2.5059E+01	2.2004E+01
		STD	1.8687E+00	1.0563E+00	1.0990E+00	1.0182E+00	1.7773E+00
	16	AVG	2.4270E+01	2.6785E+01	2.5787E+01	2.6458E+01	2.4438E+01
		STD	1.7749E+00	9.4010E-01	1.5702E+00	1.2329E+00	1.9780E+00
	18	AVG	2.5003E+01	2.7446E+01	2.6855E+01	2.6773E+01	2.5366E+01
		STD	2.3659E+00	1.1111E+00	1.5033E+00	2.3238E+00	1.5514E+00
38,092	2	AVG	<b>1.5402E+01</b>	1.2963E+01	1.3846E+01	1.3546E+01	1.3705E+01
		STD	7.6257E-01	4.0976E-01	<b>1.0417E-02</b>	4.5647E-01	2.1328E-01
	4	AVG	1.8406E+01	1.8066E+01	1.8335E+01	1.7927E+01	1.6334E+01
		STD	1.8150E+00	8.0144E-01	2.3587E-01	7.5284E-01	1.1044E+00
	6	AVG	1.9858E+01	2.0521E+01	2.0417E+01	1.9891E+01	1.7911E+01
		STD	1.7718E+00	9.8209E-01	5.6960E-01	1.1738E+00	1.6814E+00
	12	AVG	2.1656E+01	2.4457E+01	2.3778E+01	2.4082E+01	2.2171E+01
		STD	1.6223E+00	9.0147E-01	1.6145E+00	1.6152E+00	1.6195E+00
	16	AVG	2.4075E+01	2.6534E+01	2.5590E+01	2.6587E+01	2.4074E+01
		STD	1.6939E+00	1.2584E+00	1.2455E+00	1.2201E+00	1.9278E+00
	18	AVG	2.5049E+01	2.6977E+01	2.6481E+01	2.6554E+01	2.5369E+01
		STD	2.0921E+00	9.0452E-01	1.2262E+00	1.2410E+00	1.6953E+00
86,068	2	AVG	1.5178E+01	1.6710E+01	<b>1.6731E+01</b>	1.6019E+01	1.5724E+01
		STD	3.3427E-01	2.6455E-01	1.1641E-01	1.0228E+00	1.2836E+00
	4	AVG	1.7427E+01	1.9875E+01	1.9536E+01	1.9578E+01	1.7006E+01
		STD	1.7686E+00	2.0890E+00	1.9036E+00	1.4426E+00	3.1604E+00
	6	AVG	1.9143E+01	2.0526E+01	1.9740E+01	2.0408E+01	1.7993E+01
		STD	1.8736E+00	2.6564E+00	3.3539E+00	3.0873E+00	3.0954E+00
	12	AVG	2.1071E+01	2.4087E+01	2.1381E+01	2.2957E+01	2.1852E+01
		STD	2.5240E+00	1.6310E+00	2.7945E+00	2.4905E+00	2.7815E+00
	16	AVG	2.2750E+01	2.5571E+01	2.4100E+01	2.4791E+01	2.4665E+01
		STD	3.6002E+00	1.9866E+00	2.0990E+00	2.6484E+00	2.4248E+00
	18	AVG	2.4333E+01	2.6632E+01	2.5276E+01	2.6121E+01	2.4252E+01
		STD	2.2138E+00	1.5505E+00	2.6093E+00	2.5882E+00	3.1475E+00
170,057	2	AVG	1.3505E+01	1.3619E+01	<b>1.6233E+01</b>	1.5743E+01	1.5989E+01
		STD	1.1268E+00	1.3194E+00	<b>1.7764E-01</b>	9.1626E-01	8.0962E-01
	4	AVG	1.7908E+01	1.8248E+01	1.9210E+01	1.7810E+01	1.8220E+01
		STD	1.6775E+00	1.5512E+00	6.7226E-01	1.4543E+00	1.9514E+00
	6	AVG	1.9306E+01	2.0350E+01	2.1469E+01	2.0503E+01	1.9188E+01
		STD	1.7152E+00	1.2832E+00	1.3550E+00	1.6392E+00	1.9084E+00
	12	AVG	2.3672E+01	2.4131E+01	2.5379E+01	2.4856E+01	2.2474E+01
		STD	2.1226E+00	1.9157E+00	1.8850E+00	2.1013E+00	2.6435E+00
	16	AVG	2.4800E+01	2.6165E+01	2.6705E+01	2.7230E+01	2.5273E+01
		STD	1.8292E+00	1.6078E+00	2.1586E+00	1.6927E+00	1.7392E+00
	18	AVG	2.5049E+01	2.7035E+01	2.7071E+01	2.8110E+01	2.5473E+01
		STD	2.3897E+00	1.4866E+00	1.4915E+00	1.5644E+00	2.4709E+00

**Table 11** (continued)

Image	Thres.	Item	VCSWOA	WOA	BA	CS	CBA
61,060	2	AVG	1.3884E+01	1.3183E+01	1.4867E+01	1.3281E+01	1.2860E+01
		STD	5.4384E−01	1.6621E+00	1.3692E+00	2.0230E+00	2.0075E+00
	4	AVG	1.6508E+01	1.7109E+01	1.6907E+01	1.7027E+01	1.5479E+01
		STD	1.3925E+00	1.3877E+00	1.4644E+00	1.8427E+00	2.5192E+00
	6	AVG	1.8484E+01	1.8822E+01	1.9271E+01	1.8890E+01	1.8108E+01
		STD	1.2882E+00	1.7603E+00	1.5250E+00	1.9604E+00	2.0635E+00
	12	AVG	2.2464E+01	2.4174E+01	2.4230E+01	2.3987E+01	2.2343E+01
		STD	2.1438E+00	2.1911E+00	1.3344E+00	1.6406E+00	3.1568E+00
	16	AVG	2.3939E+01	2.6533E+01	2.6404E+01	2.5781E+01	2.5068E+01
		STD	2.9817E+00	2.0090E+00	1.4375E+00	2.4686E+00	1.9827E+00
	18	AVG	2.5627E+01	2.7636E+01	2.7320E+01	2.7151E+01	2.5723E+01
		STD	2.2776E+00	1.5247E+00	1.2747E+00	2.1666E+00	2.0443E+00
175,032	2	AVG	1.3524E+01	1.4766E+01	1.5383E+01	1.5272E+01	<b>1.5537E+01</b>
		STD	3.8959E−01	1.2054E+00	3.7511E−02	3.3892E−01	5.9322E−01
	4	AVG	1.5754E+01	1.8646E+01	<b>2.0356E+01</b>	1.9651E+01	1.8942E+01
		STD	1.6555E+00	1.5270E+00	2.9627E−01	8.4606E−01	1.6884E+00
	6	AVG	1.7960E+01	2.1199E+01	2.3097E+01	2.2207E+01	2.0319E+01
		STD	1.8154E+00	1.2152E+00	6.8594E−01	1.1725E+00	1.9910E+00
	12	AVG	2.3648E+01	2.3977E+01	2.5698E+01	2.6197E+01	2.3586E+01
		STD	1.9610E+00	1.6781E+00	1.6910E+00	1.4663E+00	1.9628E+00
	16	AVG	2.5858E+01	2.6156E+01	2.7215E+01	2.7661E+01	2.4820E+01
		STD	1.9990E+00	1.3185E+00	2.0427E+00	2.1651E+00	1.9969E+00
	18	AVG	2.5432E+01	2.7299E+01	2.7602E+01	2.8041E+01	2.6381E+01
		STD	2.0126E+00	1.2310E+00	1.6108E+00	1.8014E+00	1.6936E+00
223,061	2	AVG	1.5080E+01	1.5402E+01	1.5403E+01	1.5369E+01	1.5253E+01
		STD	1.6679E+00	1.7161E−02	<b>1.4723E−02</b>	1.0240E−01	1.8501E−01
	4	AVG	1.6531E+01	1.9020E+01	1.9640E+01	1.9489E+01	1.7854E+01
		STD	3.0394E+00	4.8091E−01	<b>3.2839E−01</b>	4.5413E−01	1.2589E+00
	6	AVG	1.6743E+01	2.1258E+01	2.1421E+01	2.1104E+01	1.8141E+01
		STD	3.3762E+00	<b>4.9606E−01</b>	7.2741E−01	1.0828E+00	1.9674E+00
	12	AVG	2.3033E+01	2.4495E+01	2.5389E+01	2.5219E+01	2.2500E+01
		STD	1.4262E+00	1.5994E+00	1.1023E+00	1.1338E+00	1.9331E+00
	16	AVG	2.4610E+01	2.6106E+01	2.6615E+01	2.6965E+01	2.4468E+01
		STD	1.8484E+00	1.2718E+00	1.6195E+00	1.5873E+00	1.5348E+00
	18	AVG	2.5363E+01	2.7304E+01	2.6930E+01	2.7834E+01	2.5219E+01
		STD	1.4702E+00	1.3278E+00	8.1205E−01	1.2441E+00	1.8808E+00
19,021	2	AVG	1.5450E+01	1.4130E+01	1.3846E+01	1.3931E+01	1.3626E+01
		STD	9.1065E−01	4.2569E−01	3.0575E−01	7.0591E−01	1.0463E+00
	4	AVG	1.6878E+01	1.8872E+01	1.8946E+01	1.8744E+01	1.7852E+01
		STD	2.4115E+00	9.4882E−01	1.1093E+00	9.1329E−01	1.3193E+00
	6	AVG	1.8983E+01	2.1017E+01	2.1098E+01	2.0980E+01	1.8807E+01
		STD	2.1188E+00	9.6586E−01	1.1209E+00	1.5207E+00	1.7535E+00
	12	AVG	2.2867E+01	2.4693E+01	2.4628E+01	2.4482E+01	2.3319E+01
		STD	2.3472E+00	1.4290E+00	1.7702E+00	1.5539E+00	1.3545E+00
	16	AVG	2.5079E+01	2.7020E+01	2.6847E+01	2.7504E+01	2.5438E+01
		STD	2.0556E+00	1.3793E+00	1.8186E+00	1.2652E+00	1.9875E+00
	18	AVG	2.6227E+01	2.8093E+01	2.6960E+01	2.7801E+01	2.5510E+01
		STD	1.6849E+00	1.4210E+00	1.7548E+00	2.0122E+00	2.1284E+00

Bold are the best values

**Table 12** The SSIM comparison results of VCSWOA and other methods

Image	Thres.	Item	SCA	BLPSO	IGWO	IWOA	SCADE	
291,000	2	AVG	<b>7.0750E+01</b>	6.8577E-01	6.9009E-01	7.0093E-01	7.0022E-01	
		STD	4.0932E-02	4.4047E-02	7.9963E-02	4.4785E-02	4.0458E-02	
	4	AVG	7.8451E-01	7.7853E-01	7.8563E-01	7.8200E-01	7.7637E-01	
		STD	2.9222E-02	4.0825E-02	3.2227E-02	3.4994E-02	4.1429E-02	
	6	AVG	8.2647E-01	8.2891E-01	8.2036E-01	8.2539E-01	8.3739E-01	
		STD	<b>1.3973E-02</b>	2.7519E-02	5.6508E-02	3.5432E-02	3.6554E-02	
	12	AVG	<b>9.6328E-01</b>	9.5016E-01	9.6195E-01	9.4784E-01	9.6094E-01	
		STD	<b>3.0024E-03</b>	1.3255E-02	4.0376E-03	1.2800E-02	5.0739E-03	
	16	AVG	<b>9.7680E-01</b>	9.6795E-01	9.7410E-01	9.6552E-01	9.7308E-01	
		STD	<b>1.8180E-03</b>	6.2520E-03	3.2901E-03	7.8420E-03	4.7776E-03	
	18	AVG	<b>9.8019E-01</b>	9.7320E-01	9.7599E-01	9.6795E-01	9.7666E-01	
		STD	<b>1.5076E-03</b>	5.9712E-03	9.6273E-03	1.0099E-02	5.1768E-03	
	38,092	2	AVG	<b>6.2308E-01</b>	6.2288E-01	6.0298E-01	6.2272E-01	6.1547E-01
			STD	2.4614E-03	2.1863E-03	8.6580E-02	2.6885E-03	4.5442E-02
		4	AVG	<b>8.3939E-01</b>	8.3607E-01	8.2633E-01	8.2707E-01	8.3190E-01
			STD	<b>5.7686E-03</b>	7.0205E-03	5.4741E-02	1.1822E-02	2.4842E-02
		6	AVG	<b>9.0610E-01</b>	9.0314E-01	8.9403E-01	8.8821E-01	8.6704E-01
			STD	<b>1.8303E-03</b>	8.4161E-03	2.0440E-02	1.4146E-02	9.1687E-02
12		AVG	<b>9.2602E-01</b>	9.0919E-01	9.0245E-01	8.9843E-01	9.1824E-01	
		STD	<b>5.7827E-03</b>	1.9579E-02	8.0001E-02	1.2397E-02	8.6744E-03	
16		AVG	<b>9.4331E-01</b>	9.2835E-01	9.3737E-01	9.2707E-01	9.3673E-01	
		STD	<b>3.7487E-03</b>	1.1904E-02	1.1511E-02	9.5202E-03	9.9155E-03	
18		AVG	<b>9.5197E-01</b>	9.3895E-01	9.4432E-01	9.3188E-01	9.4418E-01	
		STD	<b>3.5307E-03</b>	1.1701E-02	7.4438E-03	1.0033E-02	1.4255E-02	
86,068		2	AVG	<b>5.9149E-01</b>	5.8995E-01	5.7178E-01	5.9107E-01	5.9094E-01
			STD	<b>0.0000E+00</b>	2.9551E-03	5.1163E-02	4.9198E-04	5.6689E-03
		4	AVG	<b>7.3581E-01</b>	7.3535E-01	6.8994E-01	7.2221E-01	7.1168E-01
			STD	2.0623E-02	2.2504E-02	1.0607E-01	1.8031E-02	<b>1.4961E-02</b>
		6	AVG	8.0293E-01	8.0109E-01	7.9468E-01	8.0326E-01	<b>8.0416E-01</b>
			STD	<b>5.3442E-03</b>	1.4904E-02	3.8238E-02	7.1383E-03	1.1158E-02
	12	AVG	<b>8.8515E-01</b>	8.0882E-01	8.8426E-01	8.0364E-01	8.6052E-01	
		STD	5.8698E-02	7.2453E-02	5.0091E-02	8.1405E-02	7.8881E-02	
	16	AVG	<b>9.3622E-01</b>	8.4816E-01	9.1945E-01	8.7446E-01	8.9950E-01	
		STD	<b>8.4199E-03</b>	7.6800E-02	5.2352E-02	5.1664E-02	7.4478E-02	
	18	AVG	<b>9.3468E-01</b>	8.8587E-01	9.1062E-01	8.8884E-01	9.0655E-01	
		STD	<b>1.8505E-02</b>	5.2156E-02	6.0175E-02	4.8963E-02	5.1292E-02	
	170,057	2	AVG	3.0783E-01	3.0303E-01	3.0515E-01	2.9158E-01	3.1472E-01
			STD	1.3500E-02	6.5662E-02	6.7872E-02	6.0551E-02	6.3481E-02
		4	AVG	5.9428E-01	5.7925E-01	5.7007E-01	<b>6.3169E-01</b>	5.7648E-01
			STD	<b>1.9756E-02</b>	9.2155E-02	8.5237E-02	5.7476E-02	1.0435E-01
		6	AVG	7.5435E-01	7.2196E-01	7.4046E-01	<b>7.6859E-01</b>	7.3305E-01
			STD	6.1642E-02	7.3403E-02	6.9059E-02	5.1298E-02	8.0715E-02
12		AVG	<b>8.7523E-01</b>	8.5637E-01	8.4788E-01	8.3779E-01	8.5440E-01	
		STD	<b>1.4766E-02</b>	2.2417E-02	4.2398E-02	2.3517E-02	3.0003E-02	
16		AVG	<b>9.1676E-01</b>	8.9721E-01	8.7888E-01	8.7322E-01	8.9544E-01	
		STD	<b>8.5209E-03</b>	2.6442E-02	4.5063E-02	2.5155E-02	2.0110E-02	
18		AVG	<b>9.3128E-01</b>	9.0198E-01	8.9513E-01	8.8833E-01	9.0643E-01	
		STD	<b>7.7082E-03</b>	2.5766E-02	3.9526E-02	2.4795E-02	2.6755E-02	



**Table 12** (continued)

Image	Thres.	Item	SCA	BLPSO	IGWO	IWOA	SCADE
61,060	2	AVG	6.1249E-01	5.9833E-01	6.0373E-01	6.0785E-01	5.9648E-01
		STD	<b>5.3193E-03</b>	3.1855E-02	3.1901E-02	1.1648E-02	3.4409E-02
	4	AVG	<b>8.2624E-01</b>	8.0688E-01	8.2157E-01	8.1638E-01	8.2428E-01
		STD	<b>6.0356E-03</b>	3.0819E-02	2.6377E-02	1.0649E-02	9.2444E-03
	6	AVG	8.9253E-01	8.8783E-01	8.8081E-01	8.8214E-01	<b>8.9307E-01</b>
		STD	<b>6.9314E-03</b>	1.2132E-02	6.4144E-02	1.7825E-02	8.7795E-03
	12	AVG	8.9537E-01	8.8738E-01	8.8872E-01	8.8321E-01	<b>8.9549E-01</b>
		STD	<b>1.1862E-02</b>	1.5930E-02	2.7100E-02	1.8845E-02	1.5305E-02
	16	AVG	<b>9.1822E-01</b>	9.0873E-01	9.1197E-01	9.0453E-01	9.1614E-01
		STD	<b>7.2328E-03</b>	1.8396E-02	1.7480E-02	1.6677E-02	1.0762E-02
	18	AVG	<b>9.2993E-01</b>	9.2100E-01	9.2380E-01	9.1697E-01	9.1827E-01
		STD	<b>6.4478E-03</b>	1.2494E-02	1.9422E-02	1.1379E-02	1.0356E-02
175,032	2	AVG	5.8057E-01	5.8009E-01	5.5525E-01	5.7998E-01	5.6445E-01
		STD	<b>2.1412E-04</b>	9.9839E-04	7.2444E-02	1.2530E-03	5.5825E-02
	4	AVG	7.4176E-01	7.3965E-01	7.3603E-01	7.4345E-01	7.3374E-01
		STD	<b>1.9383E-03</b>	8.0498E-03	1.8426E-02	7.1059E-03	2.6450E-02
	6	AVG	8.2938E-01	8.2192E-01	8.2516E-01	8.2321E-01	8.2380E-01
		STD	<b>8.8811E-03</b>	1.5585E-02	1.6730E-02	1.6116E-02	2.0313E-02
	12	AVG	<b>9.6968E-01</b>	9.5804E-01	9.3703E-01	9.4757E-01	9.6226E-01
		STD	<b>5.2624E-03</b>	1.5741E-02	6.4654E-02	1.4190E-02	9.4679E-03
	16	AVG	<b>9.8180E-01</b>	9.7513E-01	9.6484E-01	9.6418E-01	9.6687E-01
		STD	<b>3.6244E-03</b>	6.1267E-03	1.5769E-02	1.0701E-02	1.4065E-02
	18	AVG	<b>9.8587E-01</b>	9.7146E-01	9.5867E-01	9.6566E-01	9.6926E-01
		STD	<b>1.7245E-03</b>	1.5078E-02	4.0355E-02	1.8742E-02	2.3520E-02
223,061	2	AVG	5.0820E-01	4.4229E-01	4.6267E-01	4.4419E-01	4.8709E-01
		STD	7.3582E-03	1.1271E-01	1.0247E-01	1.4086E-01	2.6769E-02
	4	AVG	7.1793E-01	6.6357E-01	6.4474E-01	5.4944E-01	6.6839E-01
		STD	6.2271E-02	8.4107E-02	1.5357E-01	1.6765E-01	9.9450E-02
	6	AVG	7.8055E-01	6.7863E-01	7.1514E-01	6.4804E-01	7.2012E-01
		STD	8.3824E-02	1.3973E-01	1.1921E-01	1.5406E-01	1.3017E-01
	12	AVG	<b>9.0960E-01</b>	8.8953E-01	8.9052E-01	8.9069E-01	8.9661E-01
		STD	<b>4.6542E-03</b>	1.7343E-02	2.6912E-02	8.7706E-03	1.4244E-02
	16	AVG	<b>9.3546E-01</b>	9.2143E-01	9.1809E-01	9.1640E-01	9.2192E-01
		STD	<b>2.8794E-03</b>	9.2572E-03	2.7222E-02	9.8862E-03	1.0409E-02
	18	AVG	<b>9.4638E-01</b>	9.3282E-01	9.2849E-01	9.2252E-01	9.3089E-01
		STD	<b>2.1149E-03</b>	1.0176E-02	1.5405E-02	1.0511E-02	1.0858E-02
19,021	2	AVG	5.0150E-01	4.9367E-01	4.8862E-01	<b>5.2260E-01</b>	4.8417E-01
		STD	<b>1.0962E-02</b>	2.6513E-02	6.4508E-02	2.8011E-02	6.9677E-02
	4	AVG	6.3442E-01	6.2631E-01	<b>6.3445E-01</b>	6.1553E-01	6.3290E-01
		STD	2.0514E-02	1.6180E-02	2.5335E-02	<b>1.1524E-02</b>	2.8441E-02
	6	AVG	<b>7.3927E-01</b>	7.2084E-01	7.1990E-01	7.0949E-01	7.1848E-01
		STD	<b>8.8549E-03</b>	3.0854E-02	4.0684E-02	2.7736E-02	3.4378E-02
	12	AVG	8.9878E-01	8.8927E-01	8.9460E-01	8.9343E-01	<b>9.0646E-01</b>
		STD	<b>1.3060E-02</b>	3.0974E-02	3.8897E-02	1.9555E-02	2.1584E-02
	16	AVG	<b>9.2831E-01</b>	9.2337E-01	9.1942E-01	9.1776E-01	9.2031E-01
		STD	<b>1.0435E-02</b>	2.4393E-02	5.6828E-02	2.1612E-02	3.3894E-02
	18	AVG	9.3914E-01	9.3316E-01	9.3077E-01	9.2745E-01	<b>9.4220E-01</b>
		STD	<b>1.0910E-02</b>	2.2138E-02	4.0618E-02	1.8392E-02	1.3422E-02

Bold are the best values

**Table 13** The SSIM comparison results of VCSWOA and other methods

Image	Thres.	Item	SCA	BLPSO	IGWO	IWOA	SCADE	
291,000	2	AVG	6.1946E-01	6.0962E-01	6.0573E-01	6.1313E-01	5.7531E-01	
		STD	9.9228E-02	1.1589E-02	1.3046E-02	1.0378E-02	3.8211E-02	
	4	AVG	7.3921E-01	8.2417E-01	<b>8.1523E-01</b>	7.8385E-01	6.9818E-01	
		STD	4.5514E-02	<b>8.2364E-03</b>	1.0249E-02	4.5811E-02	7.2511E-02	
	6	AVG	7.6770E-01	8.6577E-01	<b>8.7099E-01</b>	8.6335E-01	7.7685E-01	
		STD	5.2197E-02	2.0964E-02	2.1715E-02	2.0962E-02	6.0402E-02	
	12	AVG	8.8554E-01	9.3329E-01	9.2718E-01	9.3822E-01	8.7807E-01	
		STD	4.3002E-02	1.5064E-02	1.8303E-02	1.3806E-02	4.4532E-02	
	16	AVG	9.1604E-01	9.5259E-01	9.4131E-01	9.4968E-01	9.1819E-01	
		STD	3.1284E-02	1.0160E-02	2.1185E-02	1.6484E-02	3.5560E-02	
	18	AVG	9.2403E-01	9.5773E-01	9.5130E-01	9.4874E-01	9.3249E-01	
		STD	4.5679E-02	1.0511E-02	1.6941E-02	4.3992E-02	2.2788E-02	
	38,092	2	AVG	6.2244E-01	5.6425E-01	5.8037E-01	5.7453E-01	5.7753E-01
			STD	4.3249E-02	4.5159E-02	<b>3.8395E-04</b>	1.0258E-02	1.0849E-02
		4	AVG	7.5602E-01	7.1492E-01	7.4841E-01	7.2640E-01	6.9008E-01
			STD	8.5241E-02	3.0235E-02	8.9293E-03	2.4957E-02	5.2709E-02
		6	AVG	8.1024E-01	7.9673E-01	8.2543E-01	7.9136E-01	7.4565E-01
			STD	6.3805E-02	2.7558E-02	1.6421E-02	3.2382E-02	4.2548E-02
12		AVG	8.4203E-01	8.8224E-01	8.8065E-01	8.8065E-01	8.4099E-01	
		STD	3.3746E-02	1.7476E-02	2.6199E-02	3.0004E-02	4.1269E-02	
16		AVG	8.7294E-01	9.0736E-01	9.0275E-01	9.1150E-01	8.7610E-01	
		STD	3.3762E-02	1.4946E-02	2.0977E-02	1.9038E-02	3.0696E-02	
18		AVG	8.9236E-01	9.1429E-01	9.1733E-01	9.1195E-01	8.8960E-01	
		STD	3.2714E-02	1.3605E-02	1.7159E-02	2.2826E-02	2.4152E-02	
86,068		2	AVG	5.9060E-01	5.0924E-01	5.0634E-01	4.7694E-01	4.6222E-01
			STD	3.1461E-02	3.7387E-03	5.5275E-03	5.3351E-02	5.1335E-02
		4	AVG	7.0262E-01	6.9369E-01	6.7428E-01	6.7969E-01	5.4352E-01
			STD	4.6485E-02	8.3645E-02	7.2661E-02	6.3391E-02	1.4312E-01
		6	AVG	7.6044E-01	7.1886E-01	6.7936E-01	7.0111E-01	5.9677E-01
			STD	4.9403E-02	1.0052E-01	1.3245E-01	1.1952E-01	1.3037E-01
	12	AVG	7.2788E-01	8.2104E-01	7.4037E-01	7.9400E-01	7.6571E-01	
		STD	9.5552E-02	<b>4.7243E-02</b>	1.0278E-01	7.2176E-02	8.2964E-02	
	16	AVG	7.7526E-01	8.6185E-01	8.1914E-01	8.4280E-01	8.3317E-01	
		STD	1.0349E-01	4.5636E-02	6.1815E-02	7.3580E-02	6.5863E-02	
	18	AVG	8.2417E-01	8.8461E-01	8.4393E-01	8.6901E-01	8.2128E-01	
		STD	6.2206E-02	2.6121E-02	7.2092E-02	5.7395E-02	8.9906E-02	
	170,057	2	AVG	2.9228E-01	4.4150E-01	5.0363E-01	4.9095E-01	<b>5.0893E-01</b>
			STD	8.8439E-02	7.8113E-02	<b>1.3179E-02</b>	1.8736E-02	2.1368E-02
		4	AVG	6.1598E-01	6.0809E-01	6.3059E-01	5.9935E-01	6.2060E-01
			STD	1.1359E-01	4.4607E-02	2.4905E-02	4.4062E-02	5.3154E-02
		6	AVG	6.8010E-01	6.8036E-01	7.1607E-01	6.9188E-01	6.6296E-01
			STD	8.4881E-02	3.7774E-02	3.1906E-02	4.3949E-02	4.9811E-02
12		AVG	7.8294E-01	7.9229E-01	8.2281E-01	8.1267E-01	7.5666E-01	
		STD	5.0065E-02	4.4907E-02	3.9594E-02	4.6353E-02	6.3464E-02	
16		AVG	8.0790E-01	8.3700E-01	8.4904E-01	8.6385E-01	8.2014E-01	
		STD	4.2569E-02	3.3225E-02	4.1804E-02	3.1851E-02	3.8581E-02	
18		AVG	8.1488E-01	8.5308E-01	8.5741E-01	8.7637E-01	8.2242E-01	
		STD	5.2113E-02	2.9931E-02	2.7588E-02	3.0477E-02	5.4885E-02	

**Table 13** (continued)

Image	Thres.	Item	SCA	BLPSO	IGWO	IWOA	SCADE
61,060	2	AVG	5.6909E-01	6.8293E-01	<b>6.9395E-01</b>	6.7246E-01	6.5617E-01
		STD	3.5898E-02	3.7547E-02	3.2108E-02	5.5533E-02	5.5491E-02
	4	AVG	7.1777E-01	7.5946E-01	7.5537E-01	7.6000E-01	7.2231E-01
		STD	6.2687E-02	3.4992E-02	4.3028E-02	3.0975E-02	6.0069E-02
	6	AVG	7.8982E-01	8.0834E-01	8.1478E-01	8.0187E-01	7.7633E-01
		STD	5.3734E-02	3.8980E-02	3.1489E-02	3.9574E-02	5.2972E-02
	12	AVG	8.5813E-01	8.7735E-01	8.7750E-01	8.7378E-01	8.5724E-01
		STD	3.6994E-02	2.6488E-02	2.2433E-02	2.2273E-02	3.3585E-02
	16	AVG	8.7319E-01	8.9806E-01	8.9826E-01	8.9485E-01	8.8762E-01
		STD	4.0437E-02	2.3194E-02	1.6524E-02	2.8387E-02	2.2206E-02
	18	AVG	8.9267E-01	9.1142E-01	9.0682E-01	9.0403E-01	8.8765E-01
		STD	2.6672E-02	1.5608E-02	1.6757E-02	2.2163E-02	2.8638E-02
175,032	2	AVG	5.7654E-01	5.7659E-01	6.2279E-01	6.1642E-01	<b>6.2996E-01</b>
		STD	1.4813E-02	8.1274E-02	2.1352E-03	1.8952E-02	3.1700E-02
	4	AVG	6.7135E-01	7.6775E-01	<b>8.3382E-01</b>	8.0864E-01	7.8047E-01
		STD	5.6142E-02	6.4600E-02	8.8566E-03	2.9843E-02	7.2086E-02
	6	AVG	7.5544E-01	8.4872E-01	8.9854E-01	8.7711E-01	8.1874E-01
		STD	3.8021E-02	3.6189E-02	1.4764E-02	3.1345E-02	7.0547E-02
	12	AVG	8.9911E-01	9.0691E-01	9.3376E-01	9.4105E-01	8.9900E-01
		STD	4.4068E-02	3.3551E-02	2.4482E-02	1.9067E-02	4.7434E-02
	16	AVG	9.3458E-01	9.3965E-01	9.4798E-01	9.5134E-01	9.1543E-01
		STD	2.9545E-02	1.6755E-02	2.4440E-02	3.3991E-02	3.9050E-02
	18	AVG	9.2402E-01	9.5289E-01	9.5186E-01	9.5695E-01	9.3896E-01
		STD	3.8323E-02	1.3194E-02	1.7363E-02	1.8245E-02	2.7126E-02
223,061	2	AVG	4.3255E-01	5.9101E-01	5.9125E-01	5.9020E-01	<b>5.9181E-01</b>
		STD	8.5152E-02	<b>1.2020E-03</b>	1.7262E-03	5.0076E-03	2.3584E-02
	4	AVG	5.1063E-01	7.0411E-01	7.2625E-01	7.3405E-01	7.2174E-01
		STD	1.3311E-01	1.5043E-02	2.0017E-02	2.5265E-02	4.7389E-02
	6	AVG	5.5316E-01	7.9430E-01	7.9417E-01	7.8915E-01	7.2293E-01
		STD	1.2672E-01	1.6546E-02	2.5729E-02	2.8980E-02	6.1359E-02
	12	AVG	8.4524E-01	8.6297E-01	8.7568E-01	8.8219E-01	8.3590E-01
		STD	3.2835E-02	2.8562E-02	2.1970E-02	1.8716E-02	3.6741E-02
	16	AVG	8.7860E-01	8.9577E-01	8.9501E-01	9.0154E-01	8.6872E-01
		STD	2.3706E-02	1.9861E-02	2.3738E-02	2.2749E-02	3.2460E-02
	18	AVG	8.8383E-01	9.0938E-01	9.0298E-01	9.1203E-01	8.8178E-01
		STD	2.8633E-02	1.7344E-02	1.2031E-02	1.6716E-02	2.9742E-02
19,021	2	AVG	4.9638E-01	3.2640E-01	3.0758E-01	3.1489E-01	2.9347E-01
		STD	3.3653E-02	2.8324E-02	2.0051E-02	4.9948E-02	6.9040E-02
	4	AVG	5.8309E-01	6.1460E-01	6.1863E-01	6.1424E-01	6.2140E-01
		STD	6.3368E-02	4.7882E-02	7.8348E-02	6.3777E-02	9.0202E-02
	6	AVG	6.5350E-01	7.2726E-01	7.3746E-01	7.3561E-01	6.5244E-01
		STD	5.6019E-02	5.4658E-02	6.8044E-02	7.1856E-02	9.6081E-02
	12	AVG	8.0363E-01	8.3915E-01	8.4465E-01	8.4439E-01	8.1150E-01
		STD	9.1751E-02	4.8262E-02	5.5329E-02	4.3168E-02	5.0831E-02
	16	AVG	8.4832E-01	8.8766E-01	8.8663E-01	9.0301E-01	8.6395E-01
		STD	5.7471E-02	2.8272E-02	4.7704E-02	3.0503E-02	4.9316E-02
	18	AVG	8.7734E-01	9.0627E-01	8.8445E-01	8.9725E-01	8.5547E-01
		STD	3.9458E-02	3.0534E-02	4.6023E-02	5.2585E-02	5.7292E-02

Bold are the best values

**Table 14** The FSIM comparison results of VCSWOA and other methods

Image	Thres.	Item	VCSWOA	WOA	BA	CS	CBA
291,000	2	AVG	7.0070E-01	6.9890E-01	6.9549E-01	7.0450E-01	7.0290E-01
		STD	1.1661E-02	9.4608E-03	5.1055E-02	<b>7.9145E-03</b>	2.4177E-02
	4	AVG	7.7925E-01	7.7417E-01	7.7789E-01	7.7352E-01	7.7117E-01
		STD	2.3654E-02	3.0673E-02	3.0574E-02	3.2551E-02	3.1773E-02
	6	AVG	8.1991E-01	8.2828E-01	8.1425E-01	8.2040E-01	8.3567E-01
		STD	<b>1.6554E-02</b>	2.1939E-02	4.9927E-02	3.0920E-02	2.9815E-02
	12	AVG	9.5748E-01	9.5302E-01	9.5986E-01	9.5118E-01	<b>9.6234E-01</b>
		STD	<b>4.3092E-03</b>	1.1912E-02	6.0902E-03	1.0445E-02	5.4623E-03
	16	AVG	9.7197E-01	9.6682E-01	9.7320E-01	9.6783E-01	<b>9.7397E-01</b>
		STD	<b>3.5724E-03</b>	8.2113E-03	4.5181E-03	8.4288E-03	6.3335E-03
	18	AVG	9.7550E-01	9.7340E-01	9.7713E-01	9.7320E-01	<b>9.7795E-01</b>
		STD	<b>4.7209E-03</b>	6.1495E-03	7.0184E-03	6.5624E-03	6.1864E-03
38,092	2	AVG	7.8783E-01	7.8765E-01	7.7250E-01	7.8747E-01	7.8254E-01
		STD	5.0869E-04	1.7996E-03	5.8843E-02	2.1247E-03	2.8013E-02
	4	AVG	<b>9.1677E-01</b>	9.1325E-01	9.1084E-01	9.1059E-01	9.0919E-01
		STD	<b>2.1157E-03</b>	8.0268E-03	2.6569E-02	8.1979E-03	1.6676E-02
	6	AVG	<b>9.4553E-01</b>	9.4298E-01	9.4023E-01	9.3557E-01	9.2596E-01
		STD	<b>8.7705E-04</b>	4.0596E-03	9.3801E-03	8.9414E-03	4.7719E-02
	12	AVG	<b>9.5018E-01</b>	9.3429E-01	9.3533E-01	9.2988E-01	9.4605E-01
		STD	<b>4.5188E-03</b>	1.6393E-02	5.4889E-02	9.4892E-03	5.8335E-03
	16	AVG	<b>9.6563E-01</b>	9.5312E-01	9.6076E-01	9.5154E-01	9.5948E-01
		STD	<b>3.3109E-03</b>	8.8835E-03	8.9581E-03	7.6994E-03	9.5660E-03
	18	AVG	<b>9.7156E-01</b>	9.6001E-01	9.6568E-01	9.5441E-01	9.6485E-01
		STD	<b>2.4592E-03</b>	7.8032E-03	6.7922E-03	9.1200E-03	1.2665E-02
86,068	2	AVG	6.9772E-01	6.9756E-01	6.8708E-01	6.9776E-01	6.9753E-01
		STD	<b>4.5168E-16</b>	1.3138E-03	2.7579E-02	5.4580E-05	4.1799E-03
	4	AVG	<b>8.1103E-01</b>	8.0925E-01	7.7829E-01	8.0213E-01	7.9413E-01
		STD	1.2264E-02	1.2592E-02	7.2398E-02	1.0679E-02	<b>1.0241E-02</b>
	6	AVG	<b>8.6375E-01</b>	8.6105E-01	8.5829E-01	8.6319E-01	8.6342E-01
		STD	<b>3.8694E-03</b>	9.2373E-03	2.6310E-02	5.4492E-03	6.9830E-03
	12	AVG	<b>9.2535E-01</b>	8.6999E-01	9.2520E-01	8.6717E-01	9.0718E-01
		STD	4.2958E-02	<b>5.3628E-02</b>	3.5500E-02	5.8894E-02	5.8320E-02
	16	AVG	<b>9.6238E-01</b>	8.9641E-01	9.5029E-01	9.1650E-01	9.3599E-01
		STD	<b>5.5611E-03</b>	5.6312E-02	3.6110E-02	3.8206E-02	5.5433E-02
	18	AVG	<b>9.6211E-01</b>	9.2558E-01	9.4269E-01	9.2796E-01	9.4129E-01
		STD	<b>1.1611E-02</b>	3.6864E-02	4.2241E-02	3.6018E-02	3.8895E-02
170,057	2	AVG	6.4696E-01	6.4337E-01	6.4547E-01	6.4142E-01	<b>6.4752E-01</b>
		STD	5.3170E-03	2.0947E-02	2.2744E-02	2.1008E-02	2.0341E-02
	4	AVG	<b>7.9878E-01</b>	7.7579E-01	7.7825E-01	7.8679E-01	7.7892E-01
		STD	1.4397E-02	3.3107E-02	4.3738E-02	1.9850E-02	3.5195E-02
	6	AVG	<b>8.5724E-01</b>	8.3689E-01	8.5337E-01	8.4393E-01	8.5500E-01
		STD	<b>8.5633E-03</b>	3.4431E-02	1.3274E-02	2.0593E-02	1.8953E-02
	12	AVG	<b>9.2135E-01</b>	8.9727E-01	8.8950E-01	8.7737E-01	9.0005E-01
		STD	<b>1.1982E-02</b>	2.4365E-02	4.7029E-02	2.4043E-02	2.5985E-02
	16	AVG	<b>9.5452E-01</b>	9.3156E-01	9.1476E-01	9.0949E-01	9.3388E-01
		STD	<b>7.0951E-03</b>	2.4275E-02	4.4259E-02	2.3961E-02	1.7933E-02
	18	AVG	<b>9.6466E-01</b>	9.3480E-01	9.2970E-01	9.2304E-01	9.3848E-01
		STD	<b>4.9502E-03</b>	2.3498E-02	3.7675E-02	2.3890E-02	2.6902E-02

**Table 14** (continued)

Image	Thres.	Item	VCSWOA	WOA	BA	CS	CBA
61,060	2	AVG	7.1748E-01	<b>7.0891E-01</b>	7.2519E-01	7.1445E-01	7.1589E-01
		STD	<b>8.1343E-03</b>	3.5622E-02	1.9980E-02	1.2501E-02	2.9874E-02
	4	AVG	<b>8.5331E-01</b>	8.3927E-01	8.4565E-01	8.4551E-01	8.5010E-01
		STD	<b>7.3224E-03</b>	1.9380E-02	1.8130E-02	9.1219E-03	1.1118E-02
	6	AVG	8.9331E-01	8.9483E-01	8.8594E-01	8.9435E-01	<b>9.0592E-01</b>
		STD	<b>1.2214E-02</b>	1.4995E-02	3.8322E-02	1.5642E-02	1.4075E-02
	12	AVG	8.9958E-01	8.9836E-01	8.9630E-01	8.9632E-01	<b>9.0489E-01</b>
		STD	1.4515E-02	1.5846E-02	3.0335E-02	<b>1.3909E-02</b>	2.0093E-02
	16	AVG	9.3040E-01	9.2195E-01	9.2595E-01	9.1989E-01	<b>9.3237E-01</b>
		STD	1.2679E-02	1.9575E-02	1.6986E-02	1.4124E-02	<b>1.1164E-02</b>
	18	AVG	<b>9.4228E-01</b>	9.3336E-01	9.3606E-01	9.3493E-01	9.3582E-01
		STD	1.1868E-02	1.3914E-02	2.5076E-02	<b>8.8969E-03</b>	9.6902E-03
175,032	2	AVG	6.8060E-01	6.8074E-01	6.5587E-01	6.8073E-01	6.6627E-01
		STD	2.3246E-03	5.7789E-04	5.0062E-02	<b>5.0307E-04</b>	3.7293E-02
	4	AVG	8.2631E-01	8.2370E-01	8.2037E-01	8.2639E-01	8.1918E-01
		STD	<b>8.7769E-04</b>	6.2964E-03	1.5501E-02	4.8918E-03	1.9267E-02
	6	AVG	8.8953E-01	8.7890E-01	8.8554E-01	8.7925E-01	8.7873E-01
		STD	<b>4.3267E-03</b>	1.4926E-02	1.3150E-02	1.1055E-02	2.3207E-02
	12	AVG	<b>9.7563E-01</b>	9.6847E-01	9.5743E-01	9.6348E-01	9.7316E-01
		STD	<b>5.8186E-03</b>	1.1149E-02	3.5995E-02	1.0838E-02	7.7710E-03
	16	AVG	<b>9.8546E-01</b>	9.8014E-01	9.7494E-01	9.7393E-01	9.7665E-01
		STD	<b>3.3522E-03</b>	7.3528E-03	1.2420E-02	6.7361E-03	1.0546E-02
	18	AVG	<b>9.8897E-01</b>	9.7948E-01	9.6929E-01	9.7513E-01	9.7841E-01
		STD	<b>2.1669E-03</b>	1.0156E-02	3.1243E-02	1.2187E-02	1.4986E-02
223,061	2	AVG	6.5119E-01	6.0015E-01	6.2876E-01	6.1073E-01	6.3239E-01
		STD	2.5413E-03	7.3998E-02	5.7373E-02	7.7352E-02	3.8263E-02
	4	AVG	7.9614E-01	7.4998E-01	7.4249E-01	6.7030E-01	7.5887E-01
		STD	4.0972E-02	6.9305E-02	9.7403E-02	1.0828E-01	7.0548E-02
	6	AVG	8.4644E-01	7.7189E-01	7.9972E-01	7.4799E-01	8.0293E-01
		STD	4.8518E-02	9.3150E-02	8.2070E-02	9.2415E-02	9.1564E-02
	12	AVG	<b>9.5067E-01</b>	9.3027E-01	9.3434E-01	9.3194E-01	9.3919E-01
		STD	<b>2.6151E-03</b>	1.5993E-02	2.2934E-02	7.7854E-03	1.3703E-02
	16	AVG	<b>9.6754E-01</b>	9.5286E-01	9.5179E-01	9.4867E-01	9.5570E-01
		STD	<b>2.3170E-03</b>	6.3910E-03	2.6621E-02	8.6569E-03	1.1097E-02
	18	AVG	<b>9.7397E-01</b>	9.6039E-01	9.5962E-01	9.5361E-01	9.6165E-01
		STD	<b>1.0467E-03</b>	7.2699E-03	1.3577E-02	7.6458E-03	1.0427E-02
19,021	2	AVG	6.1058E-01	6.0635E-01	6.0220E-01	6.0841E-01	5.9866E-01
		STD	<b>7.0456E-04</b>	1.5484E-02	2.1174E-02	4.2819E-03	2.0878E-02
	4	AVG	7.1348E-01	7.0338E-01	7.0856E-01	6.9980E-01	7.0737E-01
		STD	<b>1.0369E-02</b>	1.2482E-02	1.9192E-02	1.0697E-02	2.0816E-02
	6	AVG	7.9887E-01	7.7742E-01	7.7921E-01	7.6760E-01	7.7818E-01
		STD	<b>5.4582E-03</b>	2.7674E-02	4.2613E-02	2.9266E-02	2.7107E-02
	12	AVG	9.3434E-01	9.2946E-01	9.3415E-01	9.3145E-01	<b>9.3910E-01</b>
		STD	<b>5.6745E-03</b>	1.4145E-02	1.2954E-02	1.0225E-02	9.6392E-03
	16	AVG	<b>9.5381E-01</b>	9.5062E-01	9.4684E-01	9.4839E-01	9.5237E-01
		STD	<b>4.2524E-03</b>	1.2688E-02	4.2393E-02	1.3163E-02	1.4745E-02
	18	AVG	9.6131E-01	9.5524E-01	9.5745E-01	9.5494E-01	<b>9.6447E-01</b>
		STD	<b>4.3954E-03</b>	1.4416E-02	1.6545E-02	1.0629E-02	7.7567E-03

Bold are the best values

**Table 15** The FSIM comparison results of VCSWOA and other methods

Image	Thres.	Item	SCA	BLPSO	IGWO	IWOA	SCADE	
291,000	2	AVG	6.8504E-01	7.1725E-01	7.0959E-01	<b>7.2611E-01</b>	6.9056E-01	
		STD	3.9609E-02	1.3296E-02	1.7158E-02	1.5747E-02	3.5720E-02	
	4	AVG	7.3226E-01	<b>8.4928E-01</b>	8.4130E-01	8.2290E-01	7.6658E-01	
		STD	4.3904E-02	<b>7.8390E-03</b>	1.0009E-02	3.0863E-02	4.3329E-02	
	6	AVG	7.6460E-01	<b>8.8770E-01</b>	8.8268E-01	8.7471E-01	8.3043E-01	
		STD	5.3785E-02	1.7816E-02	1.9311E-02	1.8018E-02	4.0168E-02	
	12	AVG	9.1006E-01	9.4548E-01	9.3861E-01	9.4394E-01	9.0064E-01	
		STD	3.1633E-02	1.3812E-02	1.6379E-02	1.3462E-02	3.0314E-02	
	16	AVG	9.3217E-01	9.6036E-01	9.5001E-01	9.5710E-01	9.3348E-01	
		STD	2.1568E-02	1.0207E-02	1.8272E-02	1.4109E-02	2.5438E-02	
	18	AVG	9.3986E-01	9.6506E-01	9.5995E-01	9.5404E-01	9.4730E-01	
		STD	3.2963E-02	8.9836E-03	1.1006E-02	3.2786E-02	1.5031E-02	
	38,092	2	AVG	<b>7.8788E-01</b>	6.5818E-01	6.8094E-01	6.7485E-01	6.7698E-01
			STD	3.2519E-02	2.7284E-02	<b>1.9469E-04</b>	8.1337E-03	5.5071E-03
		4	AVG	8.5056E-01	7.8815E-01	8.2923E-01	8.0362E-01	7.5312E-01
			STD	5.8036E-02	2.9217E-02	4.4658E-03	2.7607E-02	4.8267E-02
		6	AVG	8.8231E-01	8.5112E-01	8.7198E-01	8.4097E-01	7.9134E-01
			STD	4.2566E-02	2.5614E-02	1.5645E-02	3.2772E-02	3.4630E-02
12		AVG	8.7283E-01	9.1330E-01	9.1122E-01	9.0927E-01	8.7771E-01	
		STD	2.9843E-02	1.4335E-02	2.0066E-02	2.7314E-02	3.6543E-02	
16		AVG	9.0118E-01	9.3464E-01	9.2872E-01	9.3779E-01	9.0212E-01	
		STD	3.3386E-02	1.4774E-02	1.6655E-02	1.5460E-02	3.0410E-02	
18		AVG	9.1941E-01	9.3920E-01	9.3943E-01	9.3621E-01	9.1739E-01	
		STD	2.8801E-02	1.1480E-02	1.2827E-02	1.9982E-02	2.1468E-02	
86,068		2	AVG	<b>6.9817E-01</b>	6.5155E-01	6.4658E-01	6.2517E-01	6.0191E-01
			STD	2.4264E-02	7.0345E-03	8.4831E-03	4.4489E-02	4.8406E-02
		4	AVG	7.7075E-01	7.7119E-01	7.5884E-01	7.6311E-01	6.5990E-01
			STD	4.0727E-02	6.4022E-02	5.1197E-02	4.7038E-02	8.8118E-02
		6	AVG	8.1552E-01	8.0059E-01	7.7385E-01	7.8179E-01	7.0825E-01
			STD	4.4406E-02	6.0239E-02	8.8061E-02	8.0707E-02	8.9830E-02
	12	AVG	8.1078E-01	8.7711E-01	8.2187E-01	8.5489E-01	8.3247E-01	
		STD	6.5279E-02	3.8091E-02	7.4580E-02	5.2587E-02	6.8163E-02	
	16	AVG	8.3807E-01	9.0701E-01	8.7482E-01	8.9038E-01	8.8604E-01	
		STD	8.4103E-02	3.2650E-02	4.4935E-02	5.4829E-02	4.6049E-02	
	18	AVG	8.7553E-01	9.2209E-01	8.9527E-01	9.1039E-01	8.7737E-01	
		STD	4.8306E-02	2.0764E-02	5.3433E-02	4.2872E-02	6.6435E-02	
	170,057	2	AVG	6.3280E-01	5.6354E-01	6.1072E-01	6.0318E-01	6.1039E-01
			STD	2.7164E-02	<b>1.5082E-02</b>	1.0571E-03	1.5745E-02	9.8482E-03
		4	AVG	7.3469E-01	6.8375E-01	7.0728E-01	6.8063E-01	6.7538E-01
			STD	4.4299E-02	3.4373E-02	<b>1.3411E-02</b>	2.5465E-02	4.4694E-02
		6	AVG	7.8061E-01	7.3831E-01	7.6842E-01	7.4922E-01	7.0686E-01
			STD	5.1478E-02	3.5289E-02	3.4131E-02	3.7340E-02	4.3564E-02
12		AVG	8.2199E-01	8.3324E-01	8.6113E-01	8.4981E-01	7.9377E-01	
		STD	4.5864E-02	4.1669E-02	3.9118E-02	4.7835E-02	5.5509E-02	
16		AVG	8.4286E-01	8.7519E-01	8.8293E-01	8.9642E-01	8.5377E-01	
		STD	4.0296E-02	3.2778E-02	4.2345E-02	3.0496E-02	3.4664E-02	
18		AVG	8.4958E-01	8.8883E-01	8.8822E-01	9.0903E-01	8.5540E-01	
		STD	4.8137E-02	2.8999E-02	2.7299E-02	2.8287E-02	4.7737E-02	



**Table 15** (continued)

Image	Thres.	Item	SCA	BLPSO	IGWO	IWOA	SCADE
61,060	2	AVG	6.8124E-01	7.0455E-01	6.8972E-01	6.9770E-01	6.9219E-01
		STD	3.3539E-02	1.2719E-02	1.7646E-02	1.5637E-02	2.3358E-02
	4	AVG	7.7451E-01	7.5495E-01	7.5170E-01	7.5331E-01	7.3314E-01
		STD	4.3350E-02	3.2929E-02	3.7290E-02	2.8240E-02	4.6566E-02
	6	AVG	8.3365E-01	8.0619E-01	8.1301E-01	8.1011E-01	7.8026E-01
		STD	3.3729E-02	3.5709E-02	3.2194E-02	3.6639E-02	5.4715E-02
	12	AVG	8.6080E-01	8.8946E-01	8.8433E-01	8.8246E-01	8.6747E-01
		STD	3.2775E-02	2.3408E-02	2.2919E-02	1.7405E-02	3.0230E-02
	16	AVG	8.8404E-01	9.1038E-01	9.0786E-01	9.0678E-01	8.9510E-01
		STD	3.4109E-02	2.0798E-02	1.5007E-02	2.8825E-02	2.4979E-02
	18	AVG	9.0008E-01	9.2321E-01	9.1954E-01	9.1852E-01	8.9836E-01
		STD	2.8883E-02	1.4348E-02	1.3571E-02	1.9475E-02	2.8358E-02
175,032	2	AVG	6.7289E-01	7.6164E-01	7.8741E-01	7.8519E-01	<b>7.9197E-01</b>
		STD	1.0620E-02	5.3794E-02	1.5850E-03	1.4197E-02	2.0773E-02
	4	AVG	7.2743E-01	8.7155E-01	9.1364E-01	8.9343E-01	8.6866E-01
		STD	5.6077E-02	4.2053E-02	6.1767E-03	2.3350E-02	4.9100E-02
	6	AVG	7.9945E-01	9.1370E-01	<b>9.3703E-01</b>	9.2388E-01	8.8326E-01
		STD	4.2175E-02	2.1585E-02	1.2234E-02	2.1068E-02	5.1686E-02
	12	AVG	9.3592E-01	9.4048E-01	9.5315E-01	9.5670E-01	9.3800E-01
		STD	2.9879E-02	2.1350E-02	1.5712E-02	1.1687E-02	2.4527E-02
	16	AVG	9.5400E-01	9.6008E-01	9.6393E-01	9.6712E-01	9.4663E-01
		STD	2.3395E-02	1.1611E-02	1.6449E-02	1.9518E-02	2.1149E-02
	18	AVG	9.5251E-01	9.6783E-01	9.6597E-01	9.6881E-01	9.5988E-01
		STD	2.1760E-02	8.2453E-03	1.1766E-02	1.1373E-02	1.4608E-02
223,061	2	AVG	5.8882E-01	6.9772E-01	6.9806E-01	6.9561E-01	<b>6.9891E-01</b>
		STD	7.1601E-02	<b>4.3030E-04</b>	1.2765E-03	7.7364E-03	1.9142E-02
	4	AVG	6.3998E-01	7.8809E-01	8.0422E-01	<b>8.0588E-01</b>	7.8421E-01
		STD	7.8363E-02	<b>9.3914E-03</b>	1.0819E-02	1.6162E-02	3.6719E-02
	6	AVG	6.7012E-01	<b>8.5355E-01</b>	8.5329E-01	8.4834E-01	7.8462E-01
		STD	9.3119E-02	<b>1.3016E-02</b>	2.1119E-02	2.4915E-02	5.1957E-02
	12	AVG	8.8270E-01	9.0529E-01	9.1626E-01	9.1839E-01	8.7667E-01
		STD	2.8263E-02	2.4384E-02	1.7842E-02	1.7963E-02	3.1097E-02
	16	AVG	9.0938E-01	9.2622E-01	9.2868E-01	9.3361E-01	9.0203E-01
		STD	2.3454E-02	1.8472E-02	2.2655E-02	2.1025E-02	3.1211E-02
	18	AVG	9.1604E-01	9.3827E-01	9.3255E-01	9.4110E-01	9.1249E-01
		STD	2.7712E-02	1.6411E-02	1.1320E-02	1.4023E-02	2.7069E-02
19,021	2	AVG	6.0140E-01	<b>6.5356E-01</b>	6.4706E-01	6.4792E-01	6.4120E-01
		STD	1.2928E-02	9.9495E-03	7.0396E-03	1.4862E-02	2.4277E-02
	4	AVG	6.4593E-01	7.6776E-01	<b>7.8351E-01</b>	7.7538E-01	7.3994E-01
		STD	5.1147E-02	3.4036E-02	2.2740E-02	2.7825E-02	4.6925E-02
	6	AVG	7.0133E-01	8.2950E-01	<b>8.3456E-01</b>	8.3222E-01	7.7088E-01
		STD	4.6472E-02	2.4903E-02	3.0463E-02	4.0733E-02	5.3160E-02
	12	AVG	8.6153E-01	9.0051E-01	8.9191E-01	8.9564E-01	8.7273E-01
		STD	4.8497E-02	2.2729E-02	3.3421E-02	2.7298E-02	3.0208E-02
	16	AVG	8.9911E-01	9.2804E-01	9.2647E-01	9.3556E-01	9.0567E-01
		STD	3.3839E-02	2.0246E-02	2.3065E-02	1.6082E-02	3.3119E-02
	18	AVG	9.1525E-01	9.4142E-01	9.2670E-01	9.3858E-01	9.0330E-01
		STD	2.6264E-02	1.4152E-02	2.1946E-02	1.9481E-02	3.5614E-02

Bold are the best values

**Table 16** The PSNR comparison results of VCSWOA and other methods

Thres.	VCSWOA	WOA	BA	CS	CBA
2					
+/-/=		3/0/5	5/0/3	3/0/5	5/0/3
Mean	3.0000	5.8750	6.8750	4.3750	5.1250
Rank	1	5	9	3	4
4					
+/-/=		3/0/5	1/0/7	6/1/1	2/0/6
Mean	2.5000	4.6250	5.2500	5.2500	4.8750
Rank	1	3	6	6	4
6					
+/-/=		4/0/4	3/0/5	6/0/2	4/0/4
Mean	1.3750	5.1250	4.1250	5.3750	3.5000
Rank	1	5	3	6	2
12					
+/-/=		7/0/1	4/0/4	7/0/1	3/1/4
Mean	1.2500	4.1250	3.2500	4.5000	2.1250
Rank	1	4	3	5	2
16					
+/-/=		7/0/1	6/0/2	8/0/0	7/0/1
Mean	1.0000	3.5000	3.0000	4.8750	2.7500
Rank	1	4	3	5	2
18					
+/-/=		7/0/1	6/0/2	8/0/0	7/0/1
Mean	1.1250	3.5000	3.1250	4.6250	2.6250
Rank	1 4		3	5	2
Thres.	SCA	BLPSO	IGWO	IWOA	SCADE
2					
+/-/=	6/0/2	6/2/0	4/4/0	5/3/0	5/2/1
Mean	7.5000	6.3750	3.6250	5.8750	6.3750
Rank	10	7	2	5	7
4					
+/-/=	8/0/0	3/1/4	3/3/2	5/1/2	6/1/1
Mean	9.1250	5.1250	4.1250	5.7500	8.3750
Rank	10	5	2	8	9
6					
+/-/=	8/0/0	6/0/2	5/1/2	6/1/1	7/0/1
Mean	9.3750	5.8750	4.6250	6.0000	9.6250
Rank	9	7	4	8	10
12					
+/-/=	8/0/0	8/0/0	8/0/0	8/0/0	8/0/0
Mean	9.3750	6.7500	7.1250	7.0000	9.5000
Rank	9	6	8	7	10
16					
+/-/=	8/0/0	8/0/0	8/0/0	8/0/0	8/0/0
Mean	9.6250	6.8750	7.6250	6.5000	9.2500
Rank	10	7	8	6	9
18					
+/-/=	8/0/0	8/0/0	8/0/0	8/0/0	8/0/0
Mean	9.6250	6.6250	7.5000	6.8750	9.3750
Rank	10	6	8	7	9

**Table 17** The SSIM comparison results of VCSWOA and other methods

Thres.	VCSWOA	WOA	BA	CS	CBA
2					
+/-/=		4/0/4	1/0/7	4/1/3	1/0/7
Mean	3.1250	5.7500	6.5000	4.7500	5.7500
Rank	1	5	9	2	5
4					
+/-/=		2/0/6	2/0/6	5/1/2	2/0/6
Mean	3.2500	5.2500	5.6250	4.8750	5.5000
Rank	1	4	6	3	5
6					
+/-/=		3/0/5	3/0/5	4/0/4	3/0/5
Mean	2.8750	5.0000	5.2500	5.2500	4.2500
Rank	1	4	6	6 3	
12					
+/-/=		6/0/2	4/0/4	7/0/1	4/0/4
Mean	1.2500	3.8750	3.5000	4.6250	2.1250
Rank	1	4	3	5	2
16					
+/-/=		7/0/1 5/0/3	8/0/0	6/0/2	
Mean	1.0000	3.3750	3.1250	4.8750	2.7500
Rank	1	4	3	5	2
18					
+/-/=		7/0/1	5/0/3	8/0/0	7/0/1
Mean	1.1250	3.2500	3.2500	4.7500	2.6250
Rank	1	3	3	5	2
Thres.	SCA	BLPSO	IGWO	IWOA	SCADE
2					
3/0/5	4/3/1	4/4/0	4/4/0	4/4/0	
Mean	6.7500	6.0000	5.0000	5.7500	5.6250
Rank	10	8	3	5 4	
4					
+/-/=	7/1/0	5/2/1	3/3/2	3/1/4	4/2/2
Mean	8.0000	5.6250	4.6250	5.6250	6.6250
Rank	10	6 2	6 9		
6					
+/-/=	8/0/0	4/2/2	4/2/2	4/2/2	7/0/1
Mean	8.7500	5.0000	4.1250	5.3750	9.1250
Rank	9	4	2	8	10
12					
+/-/=	8/0/0	8/0/0	8/0/0	8/0/0	8/0/0
Mean	9.2500	7.0000	7.1250	6.6250	9.6250
Rank	9	7	8	6	10
16					
+/-/=	8/0/0	8/0/0	8/0/0	8/0/0	8/0/0
Mean	9.7500	6.8750	7.6250	6.5000	9.1250
Rank	10	7	8	6	9
18					
+/-/=	8/0/0	8/0/0	8/0/0	8/0/0	8/0/0
Mean	9.3750	6.6250	7.3750	7.0000	9.6250
Rank	9	6	8	7	10

**Table 18** The FSIM comparison results of VCSWOA and other methods

Thres.	VCSWOA	WOA	BA	CS	CBA
2					
+/-/=		1/0/7	2/1/5	2/2/4	3/1/4
Mean	4.0000	5.5000	6.1250	4.8750	5.5000
Rank	1	5	8	2	5
4					
+/-/=		6/0/2	4/0/4	6/0/2	4/0/4
Mean	2.7500	5.2500	5.2500	5.3750	5.5000
Rank	1	5	5	7	8
6					
+/-/=		5/1/2	3/0/5	5/0/3	4/2/2
Mean	3.3750	5.2500	5.1250	5.7500	4.2500
Rank	1	6	4	8	2
12					
+/-/=		6/0/2	4/0/4	6/0/2	3/2/3
Mean	1.5000	4.0000	3.3750	4.6250	1.7500
Rank	1	4	3	5	2
16					
+/-/=		6/0/2	5/0/3	7/0/1	5/0/3
Mean	1.3750	3.7500	3.2500	4.6250	2.1250
Rank	1	4	3	5	2
18					
+/-/=		6/0/2	5/1/2	7/0/1	6/0/2
Mean	1.3750	3.7500	3.0000	4.6250	2.2500
Rank	1	4	3	5	2
Thres.	SCA	BLPSO	IGWO	IWOA	SCADE
2					
+/-/=	6/0/2	4/4/0	4/4/0	4/4/0	4/3/1
Mean	6.8750	5.3750	5.1250	5.5000	6.1250
Rank	10	4	3	5	8
4					
+/-/=	8/0/0	4/3/1	4/3/1	4/3/1	4/2/2
Mean	8.1250	5.1250	4.7500	5.1250	7.7500
Rank	10	3	2	3	9
6					
+/-/=	8/0/0	4/3/1	4/3/1	4/3/1	6/0/2
Mean	8.0000	5.1250	4.5000	5.3750	8.2500
Rank	9	4	3	7	10
12					
+/-/=	8/0/0	8/0/0	8/0/0	8/0/0	8/0/0
Mean	9.6250	6.5000	7.3750	7.0000	9.2500
Rank	10	6	8	7	9
16					
+/-/=	8/0/0	8/0/0	8/0/0	8/0/0	8/0/0
Mean	9.7500	6.8750	7.6250	6.5000	9.1250
Rank	10	7	8	6	9
18					
+/-/=	8/0/0	8/0/0	8/0/0	8/0/0	8/0/0
Mean	9.5000	6.5000	7.5000	7.0000	9.5000
Rank	9	6	8	7	9

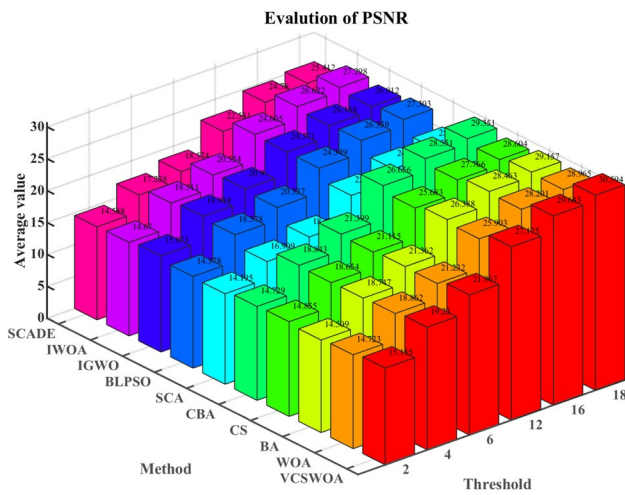


Fig. 5 Average of PSNR at each threshold level

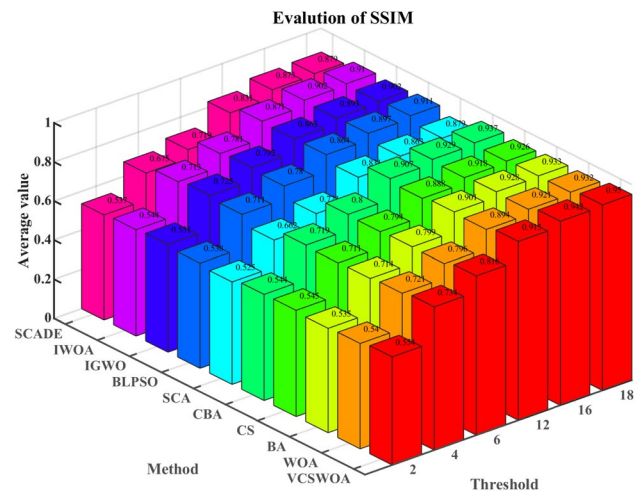


Fig. 7 Average of SSIM at each threshold level

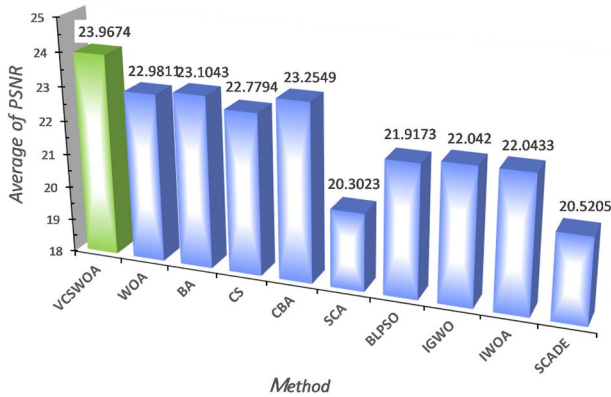


Fig. 6 Average of PSNR for all threshold levels

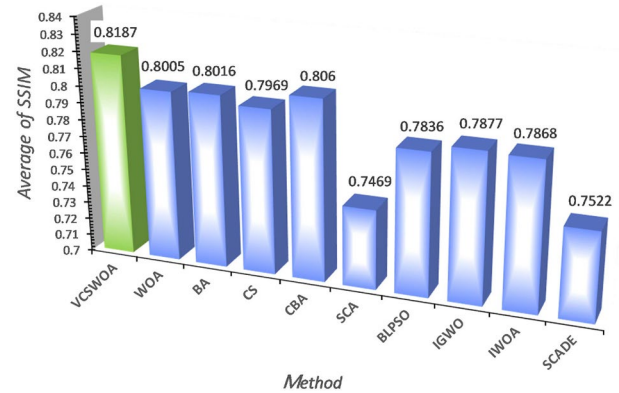


Fig. 8 Average of SSIM for all threshold levels

results. PSNR, SSIM, FSIM can be calculated from the following equations:

$$PSNR = 20 \log_{10} \left( \frac{255}{\sqrt{\frac{\sum_{i=1}^n \sum_{j=1}^m (I_{i,j} - I_{seg})^2}{N.M}}} \right) \tag{22}$$

where  $I$  and  $I_{seg}$  refers to the original image and segmented one.  $I_{i,j}$  refers to image gray level at  $(i, j)$ th pixel

$$SSIM(I, I_{seg}) = \frac{(2\mu_I \mu_{I_{seg}} + c_1)(2\sigma_{I, I_{seg}} + c_2)}{(\mu_I^2 \mu_{I_{seg}}^2 + c_1)(\sigma_I^2 + \sigma_{I_{seg}}^2 + c_2)} \tag{23}$$

$\mu_I$  and  $\mu_{I_{seg}}$  refers to image mean intensity of  $I$  and  $I_{seg}$ , respectively and,  $\sigma_I$  and  $\sigma_{I_{seg}}$  refers to the standard deviation of  $I$  and  $I_{seg}$ , respectively.

$$FSIM = \frac{\sum_{x \in \Omega} S_L(x).PC_m(x)}{\sum_{x \in \Omega} PC_m(x)} \tag{24}$$

where  $\Omega$  refers to the spatial domain of the whole image and  $S_L(x)$  and  $PC_m$  can be calculated as follows:

$$S_L(x) = [S_{PC}(x)]^\alpha [S_G(x)]^\beta \tag{25}$$

where  $\alpha, \beta$  refers to PC and GM relative important parameters and  $S_G(x)$  can be calculated as follows:

$$S_G(x) = \frac{2G_1(x).G_2(x) + T_2}{G_1^2(x).G_2^2(x) + T_2} \tag{26}$$

$$S_{PC} = \frac{2PC_1(x).PC_2(x) + T_1}{PC_1^2(x).PC_2^2(x) + T_1} \tag{27}$$

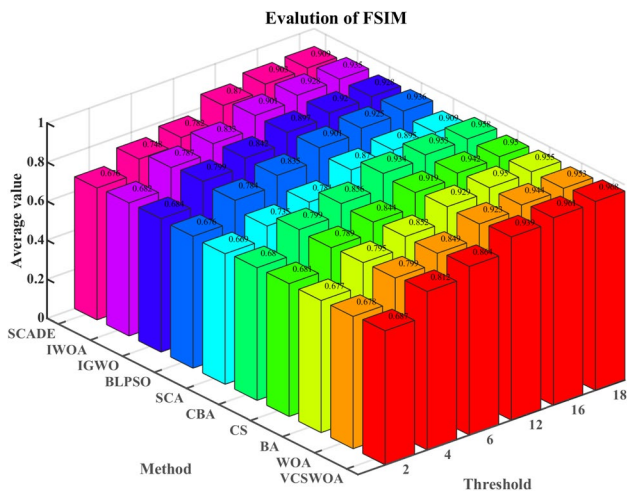


Fig. 9 Average of FSIM at each threshold level

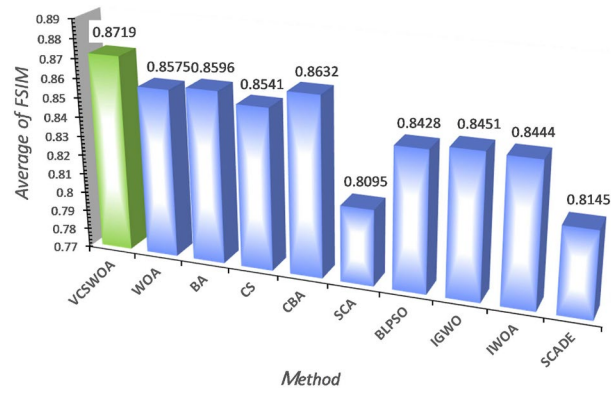
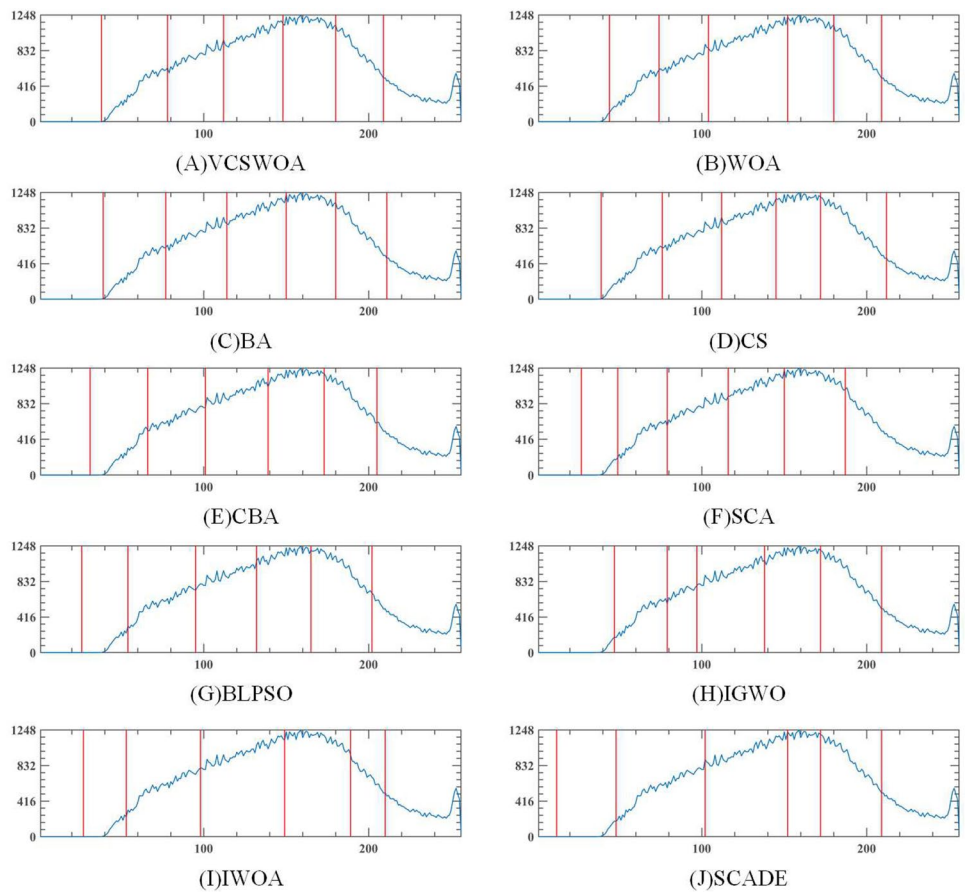


Fig. 10 Average of FSIM for all threshold levels

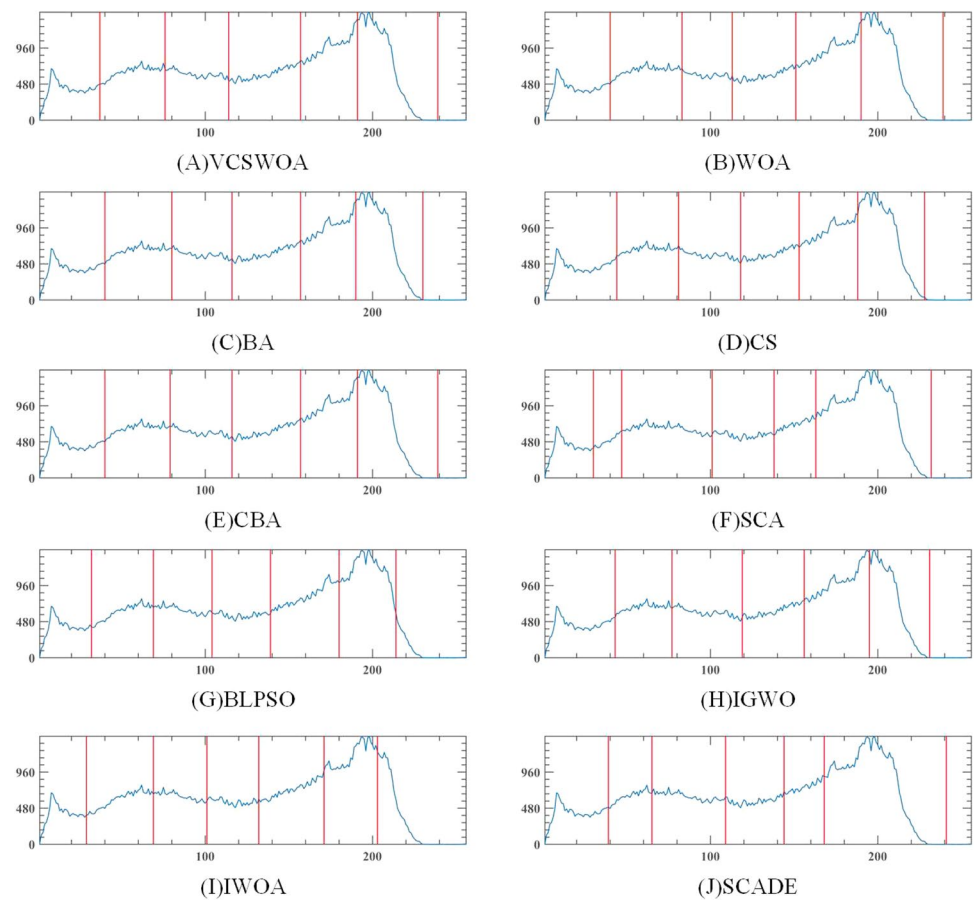
Fig. 11 Threshold values of 291,000 obtained by each algorithm at level 6



Furthermore, Figs. 5 and 6 respectively show the average PSNR for each threshold level and all threshold levels. Figures 7 and 8 respectively show the average SSIM for each

threshold level and all threshold levels. Figures 9 and 10 respectively show the average FSIM for each threshold level and all threshold levels. And, Tables 10, 11, 12, 13, 14,

**Fig. 12** Threshold values of 223,061 obtained by each algorithm at level 6



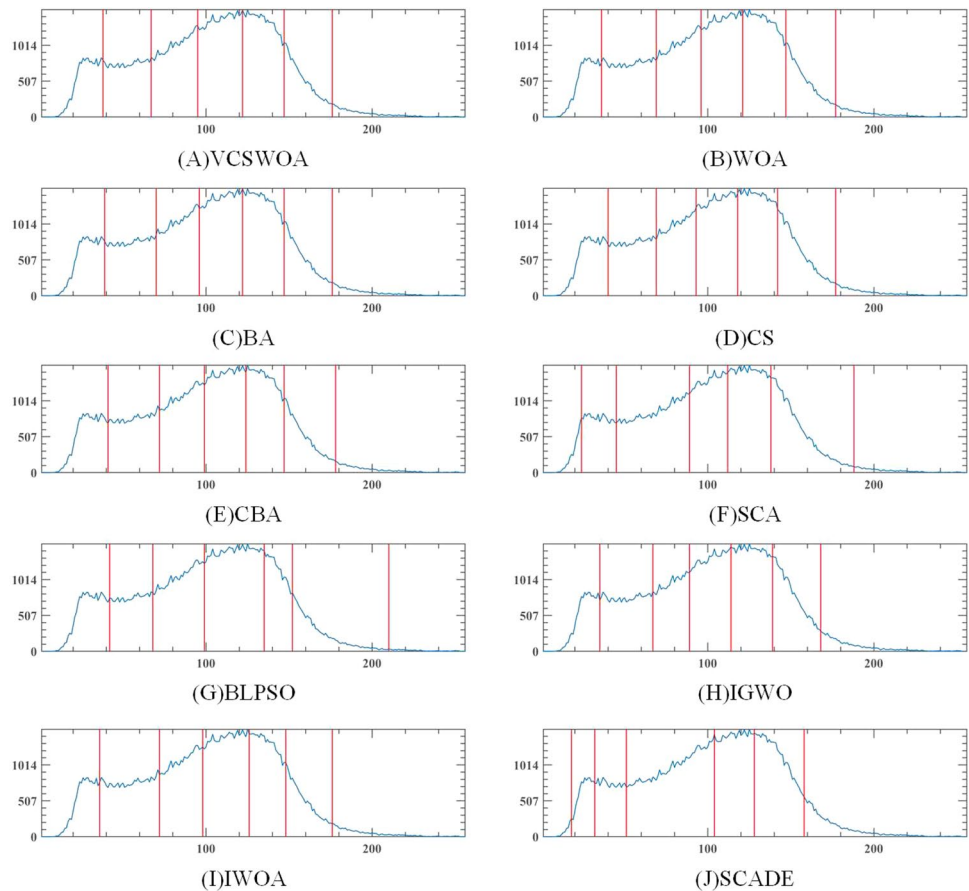
and 15 and Figs. 11, 12, 13, 14, 15, 16, 17, 18, 19, 20 and 21 show the results of VCSWOA compared with other metaheuristic algorithms.

Also, Tables 16, 17 and 18 show the ranking of compared algorithms. It can be noticed that the proposed algorithm ranked first in almost all images.

As said by our findings, the developed WOA-based technique has obtained enhanced results based on its core exploitative patterns in engineering and image processing tasks. Hence, we suggest the application of our WOA variant to problems on the evaluation of human lower limb motions [102], Lunar impact crater detection and age estimation [103], social recommendation and QoS-aware service

composition [104–106], shape registration [107], and regression tasks [108]. Also, its continuous and binary variants can be applied to gate resource allocation [109, 110], and shape analysis [111, 112]. Also, we need to apply this variant of WOA to more real-world problems and investigate its full explorative features based on more cases such as brain function prediction [113, 114], covert communication system [115–117], epidemic prevention and control [118, 119], large scale network analysis [120], energy storage planning and scheduling [121], medical diagnosis [95, 122–124], pedestrian dead reckoning [125], image dehazing [126–128], and feature selection [129–131].

**Fig. 13** Threshold values of 175,032 obtained by each algorithm at level 6



## 6 Conclusion and future works

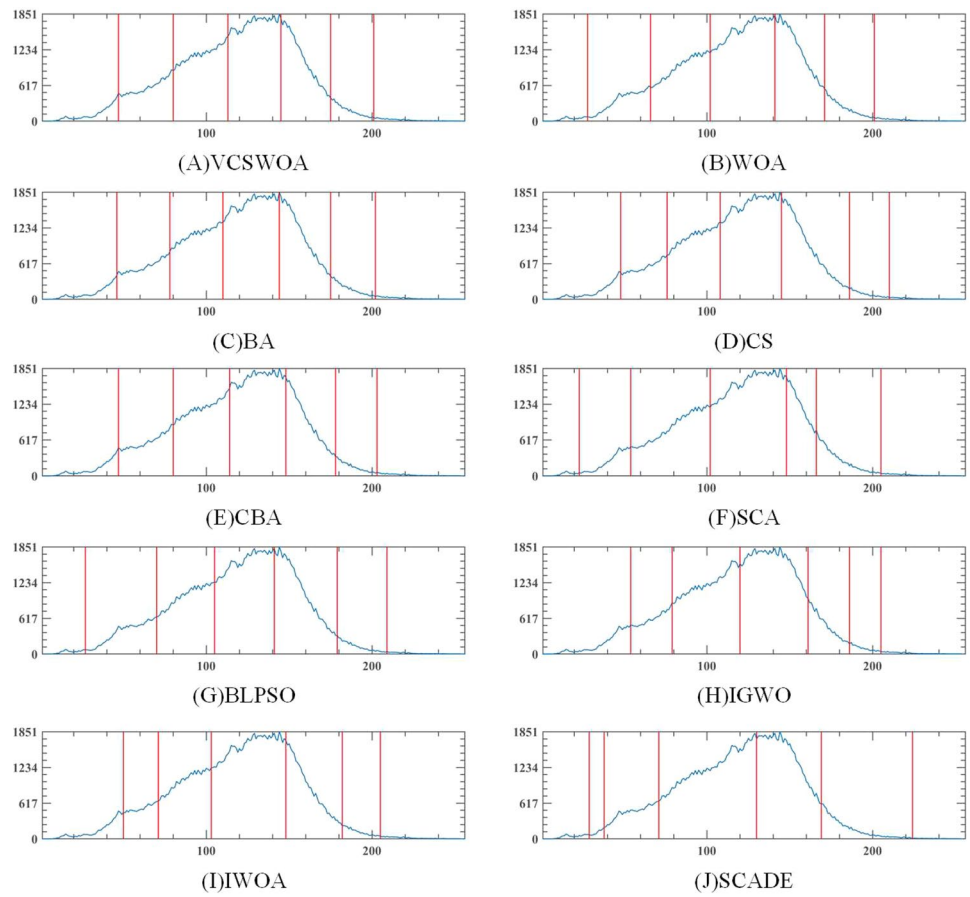
As there are some core shortcomings for WOA, such as immature convergence and stagnation, we proposed an enhanced VCSWOA method with two active cores of the WOA and VCS optimizers as a new structure. We considered a set of functions from the IEEE CEC2017 competition, and four different engineering problems are utilized to validate the efficacy of the developed VCSWOA. Also, the VCSWOA has been verified in dealing with image segmentation problems over many threshold values. We observed that the VCSWOA achieves the best results than other WOA-based algorithms, namely CWOA, OBWOA, ACWOA, BMWOA,

IWOA, BWOA, and CCMWOA. The proposed approach is also applied to several well-known methods of image cases. The results indicate the convergence speed and quality of searching has enhanced significantly based on the better balance amongst the essential diversification and intensification trends.

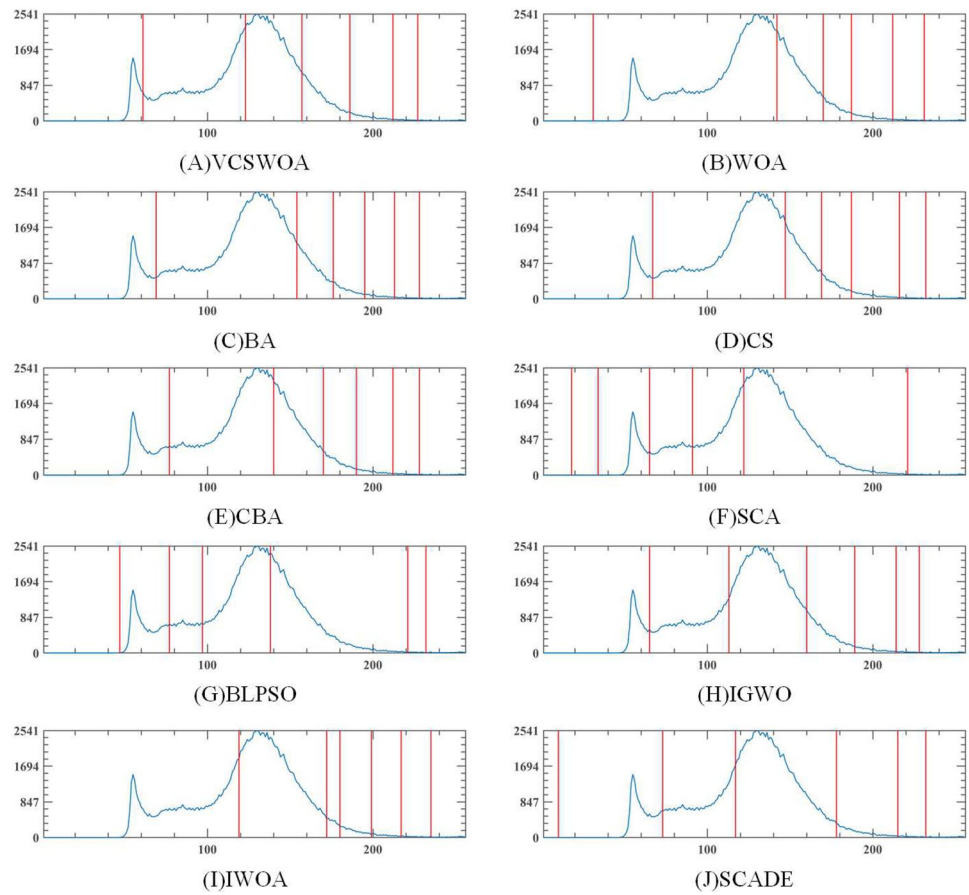
For future works, we intend to develop the binary and multi-objective version of the WOA-based method. Applying this variant to the training of neural networks is another valuable direction that is in line with the higher exploratory power of the VCSWOA.



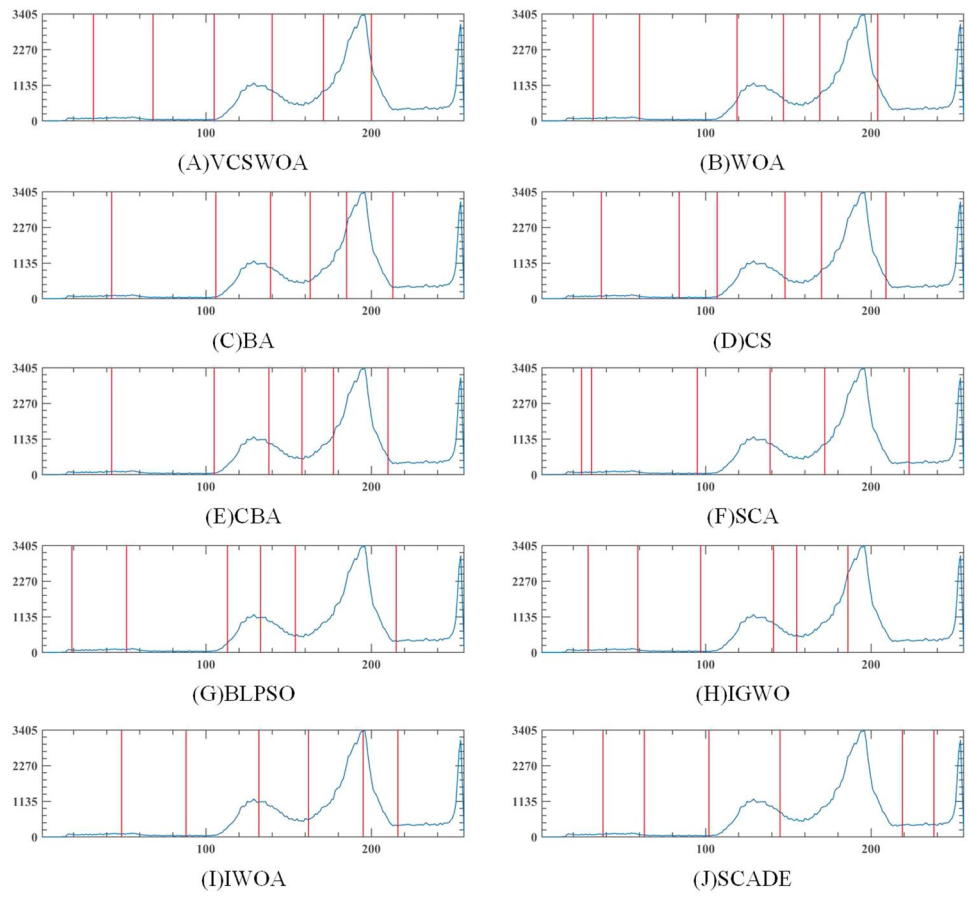
**Fig. 14** Threshold values of 170,057 obtained by each algorithm at level 6



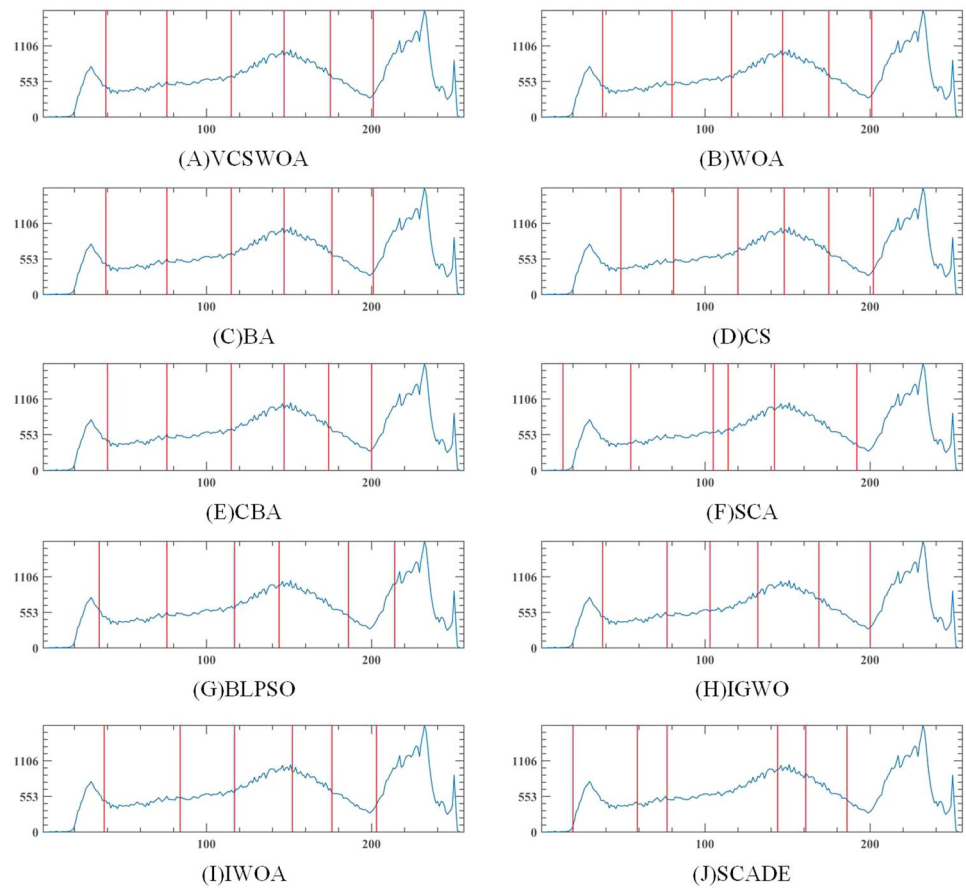
**Fig. 15** Threshold values of 86,068 obtained by each algorithm at level 6



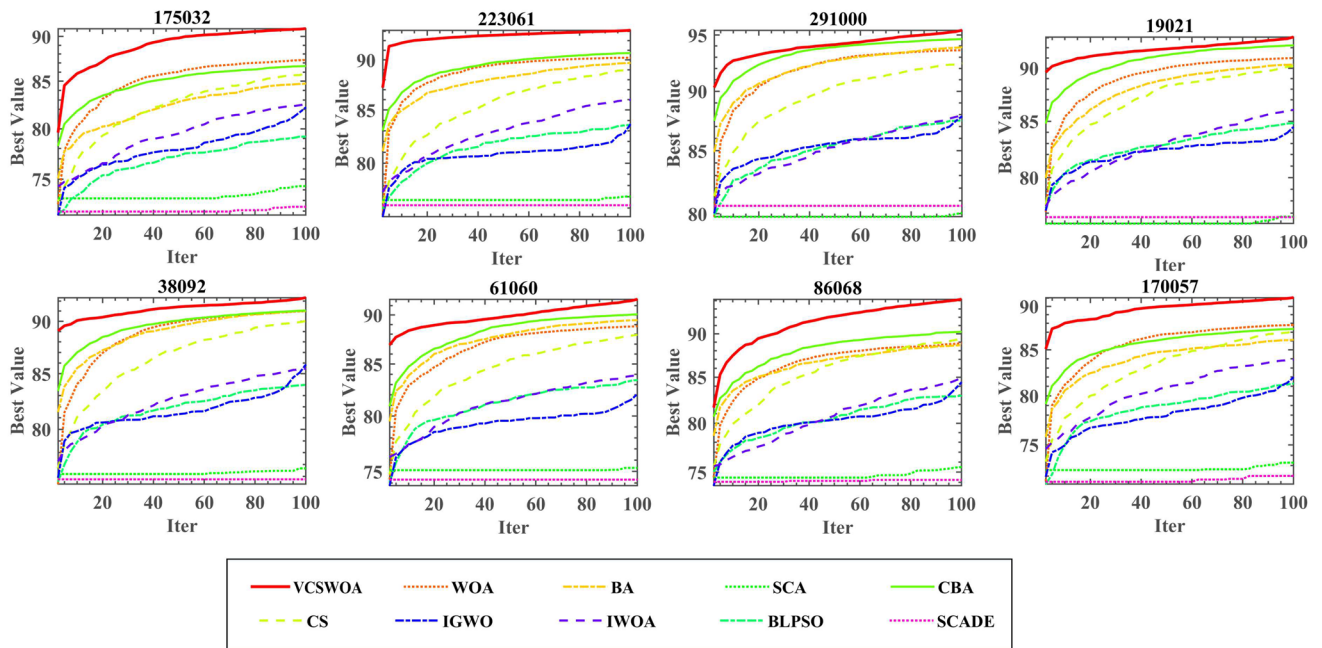
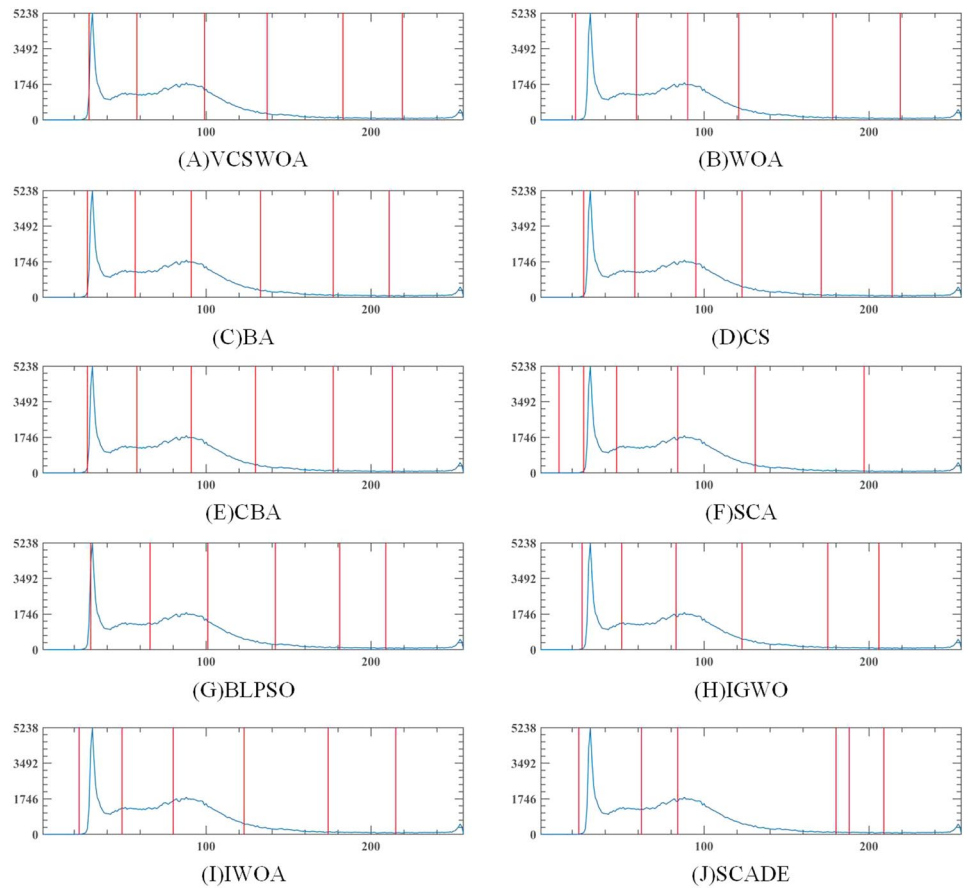
**Fig. 16** Threshold values of 61,060 obtained by each algorithm at level 6



**Fig. 17** Threshold values of 38,092 obtained by each algorithm at level 6



**Fig. 18** Threshold values of 19,021 obtained by each algorithm at level 6



**Fig. 19** Convergence curves of Kapur's entropy at threshold value 18



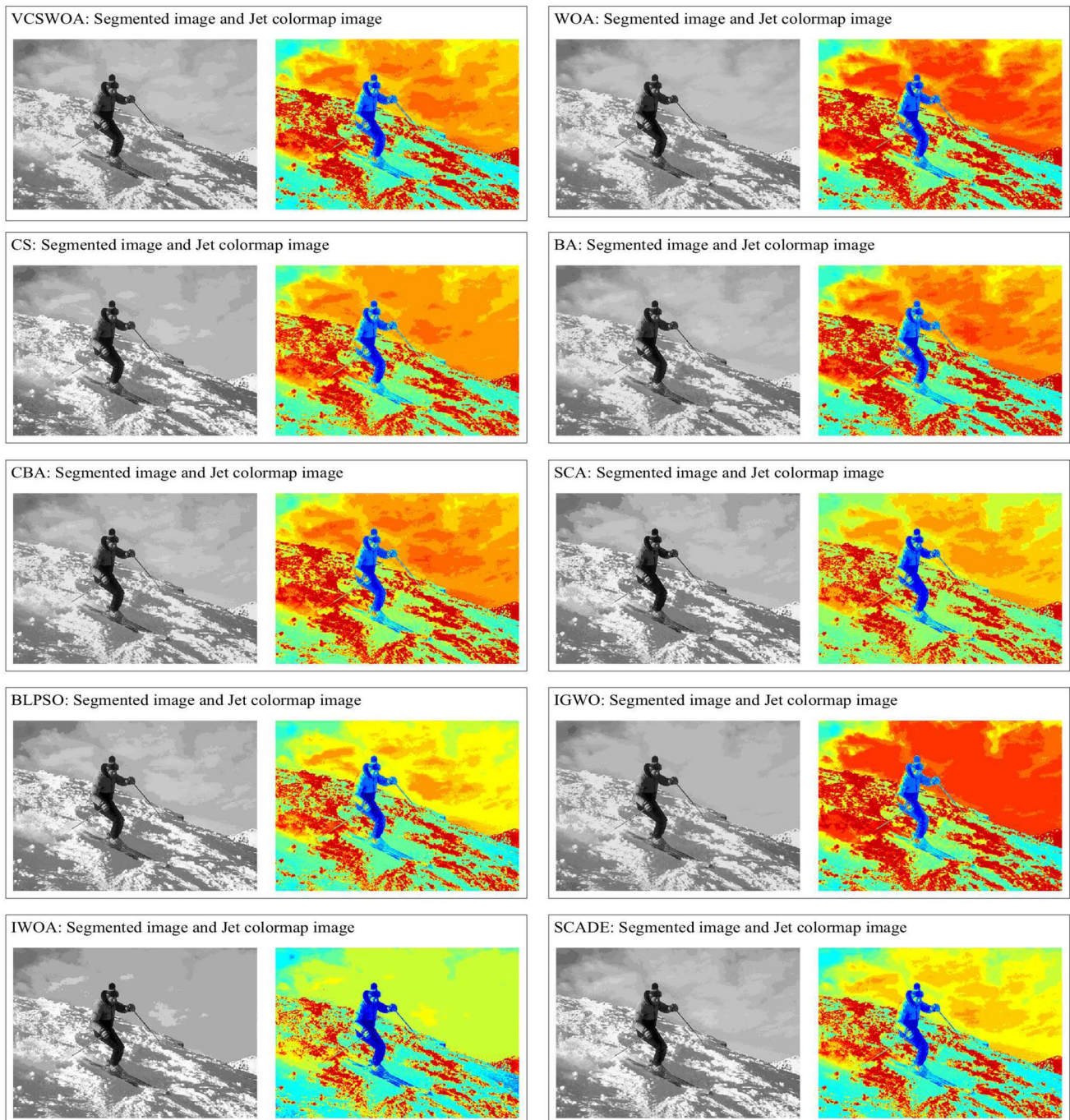


Fig. 20 Segmented results of 61,060 obtained by each algorithm at threshold value 18

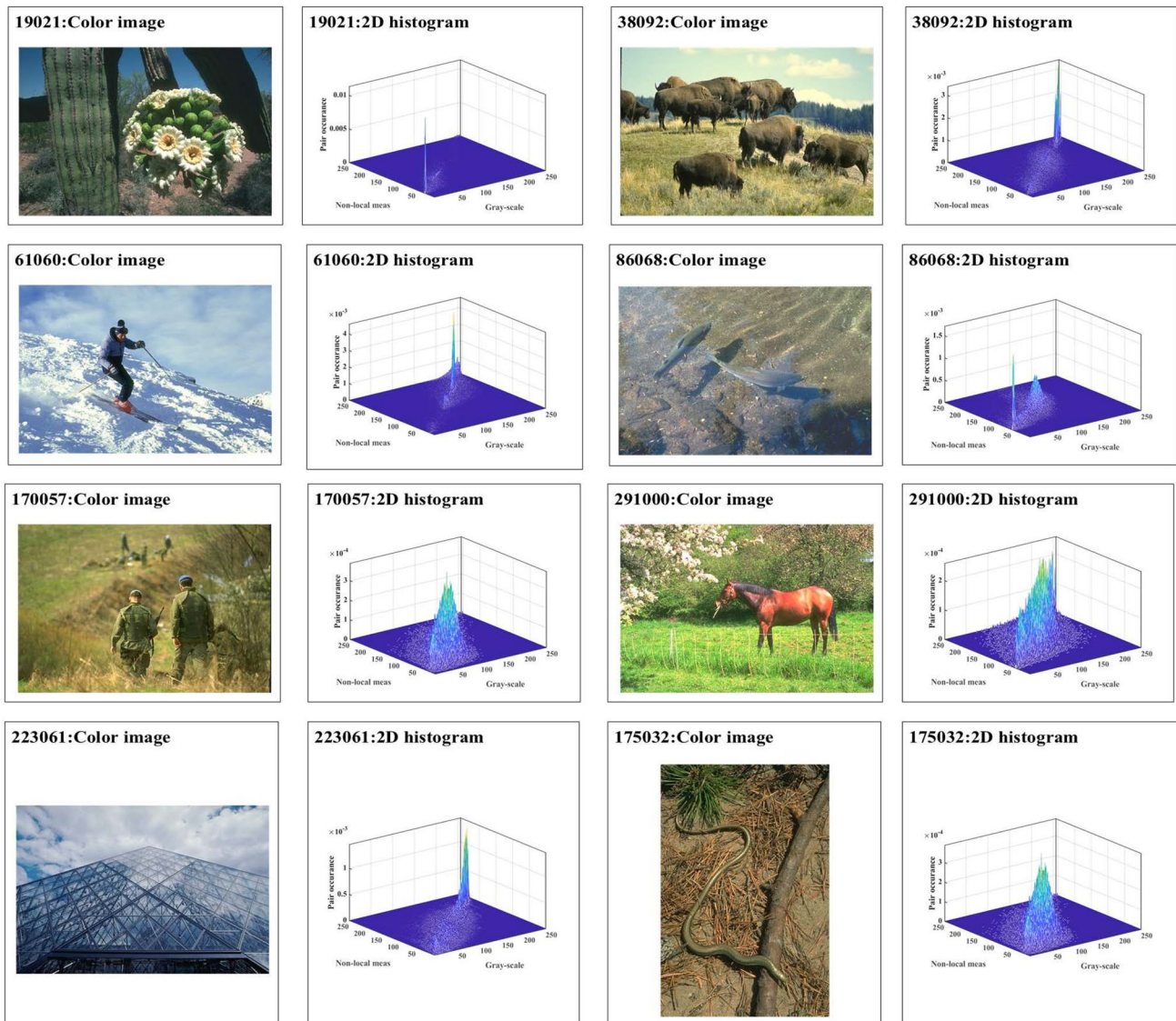


Fig. 21 Samples of the segmented images

## Declarations

**Conflict of interest** The authors declare that they have no conflict of interest.

**Ethical approval** This article does not contain any studies with human participants or animals performed by any of the authors.

**Informed consent** Informed consent was obtained from all individual participants included in the study.

## References

1. Simon D (2008) Biogeography-based optimization. *IEEE Trans Evol Comput* 12(6):702–713
2. Hassanien AE, Emary E (2018) Swarm intelligence: principles, advances, and applications. CRC Press, Boca Raton
3. Abualigah L, Gandomi AH, Elaziz MA, Hussien AG, Khasawneh AM, Alshinwan M, Houssein EH (2020) Nature-inspired optimization algorithms for text document clustering—a comprehensive analysis. *Algorithms* 13(12):345
4. Holland JH (1992) Genetic algorithms. *Sci Am* 267(1):66–73
5. Rechenberg I (1978) Evolutionsstrategien. In: Schneider B, Ranft U (eds) *Simulationsmethoden in der Medizin und Biologie. Medizinische Informatik und Statistik*, vol 8. Springer, Berlin, Heidelberg. Berthold Schneider, Ulrich Ranft. [https://doi.org/10.1007/978-3-642-81283-5\\_8](https://doi.org/10.1007/978-3-642-81283-5_8)
6. Koza JR, Koza JR (1992) Genetic programming: on the programming of computers by means of natural selection, vol 1. MIT Press, Cambridge
7. Wang T, Liu W, Zhao J, Guo X, Terzija V (2020) A rough set-based bio-inspired fault diagnosis method for electrical



- substations. *Int J Elec Power Energy Syst* 119:105961. <https://doi.org/10.1016/j.ijepes.2020.105961>
8. Kennedy J, Eberhart R (1995) Particle swarm optimization. In: *Proceedings of ICNN'95-international conference on neural networks*, vol 4. IEEE, pp 1942–1948
  9. Dorigo M, Maniezzo V, Colnani A (1996) Ant system: optimization by a colony of cooperating agents. *IEEE Trans Syst Man Cybern Part B (Cybern)* 26(1):29–41
  10. Heidari AA, Mirjalili S, Faris H, Aljarah I, Mafarja M, Chen H (2019) Harris hawks optimization: algorithm and applications. *Future Gener Comput Syst* 97:849–872
  11. Li MD, Zhao H, Weng XW, Han T (2016) A novel nature-inspired algorithm for optimization: virus colony search. *Adv Eng Softw* 92:65–88
  12. Li S, Chen H, Wang M, Heidari AA, Mirjalili S (2020) Slime mould algorithm: a new method for stochastic optimization. *Future Gener Comput Syst* 111:300–323
  13. Yang Y, Chen H, Heidari AA, Gandomi AH (2021) Hunger games search: visions, conception, implementation, deep analysis, perspectives, and towards performance shifts. *Expert Syst Appl* 177:114864
  14. Ahmadianfar I, Heidari AA, Gandomi AH, Chu X, Chen H (2021) Run beyond the metaphor: an efficient optimization algorithm based on runge kutta method. *Expert Syst Appl* 181:115079
  15. Kirkpatrick S, Gelatt CD, Vecchi MP (1983) Optimization by simulated annealing. *Science* 220(4598):671–680
  16. Rashedi E, Nezamabadi-Pour H, Saryazdi S (2009) GSA: a gravitational search algorithm. *Inf Sci* 179(13):2232–2248
  17. Rao RV, Savsani VJ, Vakharia D (2012) Teaching-learning-based optimization: an optimization method for continuous non-linear large scale problems. *Inf Sci* 183(1):1–15
  18. Glover F (1989) Tabu search-part i. *ORSA J Comput* 1(3):190–206
  19. Ba AF, Huang H, Wang M, Ye X, Gu Z, Chen H, Cai X (2020) Levy-based antlion-inspired optimizers with orthogonal learning scheme. *Eng Comput*. <https://doi.org/10.1007/s00366-020-01042-7>
  20. Liang X, Cai Z, Wang M, Zhao X, Chen H, Li C (2020) Chaotic oppositional sine–cosine method for solving global optimization problems. *Eng Comput*. <https://doi.org/10.1007/s00366-020-01083-y>
  21. Hu L, Li H, Cai Z, Lin F, Hong G, Chen H, Lu Z (2017) A new machine-learning method to prognosticate paraquat poisoned patients by combining coagulation, liver, and kidney indices. *PLoS One* 12(10):e0186427
  22. Huang H, Zhou S, Jiang J, Chen H, Li Y, Li C (2019) A new fruit fly optimization algorithm enhanced support vector machine for diagnosis of breast cancer based on high-level features. *BMC Bioinform* 20(8):1–14
  23. Li C, Hou L, Sharma BY, Li H, Chen C, Li Y, Zhao X, Huang H, Cai Z, Chen H (2018) Developing a new intelligent system for the diagnosis of tuberculous pleural effusion. *Comput Methods Programs Biomed* 153:211–225
  24. Zhao X, Zhang X, Cai Z, Tian X, Wang X, Huang Y, Chen H, Hu L (2019) Chaos enhanced grey wolf optimization wrapped elm for diagnosis of paraquat-poisoned patients. *Comput Biol Chem* 78:481–490
  25. Pang J, Zhou H, Tsai Y-C, Chou F-D (2018) A scatter simulated annealing algorithm for the bi-objective scheduling problem for the wet station of semiconductor manufacturing. *Comput Ind Eng* 123:54–66. <https://doi.org/10.1016/j.cie.2018.06.017>
  26. Zhou H, Pang J, Chen P-K, Chou F-D (2018) A modified particle swarm optimization algorithm for a batch-processing machine scheduling problem with arbitrary release times and non-identical job sizes. *Comput Ind Eng* 123:67–81. <https://doi.org/10.1016/j.cie.2018.06.018>
  27. Li Q, Chen H, Huang H, Zhao X, Cai Z, Tong C, Liu W, Tian X (2017) An enhanced grey wolf optimization based feature selection wrapped kernel extreme learning machine for medical diagnosis. *Comput Math Methods Med*. <https://doi.org/10.1155/2017/9512741>
  28. Liu T, Hu L, Ma C, Wang Z-Y, Chen H-L (2015) A fast approach for detection of erythemato-squamous diseases based on extreme learning machine with maximum relevance minimum redundancy feature selection. *Int J Syst Sci* 46(5):919–931
  29. Zhang Y, Liu R, Wang X et al (2021) Boosted binary Harris hawks optimizer and feature selection. *Eng Comput* 37:3741–3770
  30. Chen M, Zeng G, Lu K, Weng J (2019) A two-layer nonlinear combination method for short-term wind speed prediction based on elm, enn, and lstm. *IEEE Internet Things J* 6(4):6997–7010. <https://doi.org/10.1109/JIOT.2019.2913176>
  31. Ba AF, Huang H, Wang M, Ye X, Gu Z, Chen H, Cai X (2020) Levy-based antlion-inspired optimizers with orthogonal learning scheme. *Eng Comput* 1–22. <https://doi.org/10.1007/s00366-020-01042-7>
  32. Liang X, Cai Z, Wang M, Zhao X, Chen H, Li C (2020) Chaotic oppositional sine–cosine method for solving global optimization problems. *Eng Comput* 1–17
  33. Zhang H, Cai Z, Ye X, Wang M, Kuang F, Chen H, Li C, Li Y (2020) A multi-strategy enhanced salp swarm algorithm for global optimization. *Eng Comput* 1–27
  34. Zeng G-Q, Lu Y-Z, Mao W-J (2011) Modified extremal optimization for the hard maximum satisfiability problem. *J Zhejiang Univ Sci C* 12(7):589–596
  35. Zeng G, Lu Y, Dai Y, Wu Z, Mao W, Zhang Z, Zheng CJ-JIC (2012) Backbone guided extremal optimization for the hard maximum satisfiability problem. *Int J Innov Comput Inf Control* 8(12):8355–8366
  36. Cai Z, Gu J, Luo J, Zhang Q, Chen H, Pan Z, Li Y, Li C (2019) Evolving an optimal kernel extreme learning machine by using an enhanced grey wolf optimization strategy. *Expert Syst Appl* 138:112814
  37. Yu C, Chen M, Cheng K, Zhao X, Ma C, Kuang F, Chen H (2021) SGOA: annealing-behaved grasshopper optimizer for global tasks. *Eng Comput*. <https://doi.org/10.1007/s00366-020-01234-1>
  38. Shen L, Chen H, Yu Z, Kang W, Zhang B, Li H, Yang B, Liu D (2016) Evolving support vector machines using fruit fly optimization for medical data classification. *Knowl Based Syst* 96:61–75
  39. Wang M, Chen H (2020) Chaotic multi-swarm whale optimizer boosted support vector machine for medical diagnosis. *Appl Soft Comput* 88:105946
  40. Wang M, Chen H, Yang B, Zhao X, Hu L, Cai Z, Huang H, Tong C (2017) Toward an optimal kernel extreme learning machine using a chaotic moth-flame optimization strategy with applications in medical diagnoses. *Neurocomputing* 267:69–84
  41. Zeng G-Q, Chen J, Dai Y-X, Li L-M, Zheng C-W, Chen M-RJN (2015) Design of fractional order pid controller for automatic regulator voltage system based on multi-objective extremal optimization. *Neurocomputing* 160:173–184
  42. Zeng G-Q, Lu K-D, Dai Y-X, Zhang Z-J, Chen M-R, Zheng C-W, Wu D, Peng W-WJN (2014) Binary-coded extremal optimization for the design of pid controllers. *Neurocomputing* 138:180–188
  43. Zeng G-Q, Xie X-Q, Chen M-R, Weng J (2019) Adaptive population extremal optimization-based pid neural network for multivariable nonlinear control systems. *Swarm Evol Comput* 44:320–334. <https://doi.org/10.1016/j.swevo.2018.04.008>



44. Zhao X, Li D, Yang B, Chen H, Yang X, Yu C, Liu S (2015) A two-stage feature selection method with its application. *Comput Electr Eng* 47:114–125
45. Zhao X, Li D, Yang B, Ma C, Zhu Y, Chen H (2014) Feature selection based on improved ant colony optimization for online detection of foreign fiber in cotton. *Appl Soft Comput* 24:585–596
46. Pei H, Yang B, Liu J, Chang K (2020) Active surveillance via group sparse Bayesian learning. *IEEE Trans Pattern Anal Mach Intell*. <https://doi.org/10.1109/TPAMI.2020.3023092>
47. Xue X, Chen Z, Wang S, Feng Z, Duan Y, Zhou Z (2020) Value entropy: a systematic evaluation model of service ecosystem evolution. *IEEE Trans Serv Comput*. <https://doi.org/10.1109/TSC.2020.3016660>
48. Xue X, Wang SF, Zhan LJ, Feng ZY, Guo YD (2019) Social learning evolution (sle): computational experiment-based modeling framework of social manufacturing. *IEEE Trans Ind Inform* 15(6):3343–3355. <https://doi.org/10.1109/tii.2018.2871167>
49. Li J, Soladie C, Segulier R (2020) Local temporal pattern and data augmentation for micro-expression spotting. *IEEE Trans Affect Comput*. <https://doi.org/10.1109/TAFFC.2020.3023821>
50. Wang S-J, He Y, Li J, Fu X (2011) Mesnet: a convolutional neural network for spotting multi-scale micro-expression intervals in long videos. *IEEE Trans Image Process*. <https://doi.org/10.1109/TIP.2021.3064258>
51. Tu J, Lin A, Chen H, Li Y, Li C (2019) Predict the entrepreneurial intention of fresh graduate students based on an adaptive support vector machine framework. *Math Probl Eng* 2019:1–16
52. Wei Y, Ni N, Liu D, Chen H, Wang M, Li Q, Cui X, Ye H (2017) An improved grey wolf optimization strategy enhanced svm and its application in predicting the second major. *Math Probl Eng* 2017:1–12
53. Mirjalili S, Lewis A (2016) The whale optimization algorithm. *Adv Eng Softw* 95:51–67
54. Hussien AG, Hassanien AE, Houssein EH, Amin M, Azar AT (2019) New binary whale optimization algorithm for discrete optimization problems. *Eng Optim* 1–15
55. Aljarah I, Faris H, Mirjalili S (2018) Optimizing connection weights in neural networks using the whale optimization algorithm. *Soft Comput* 22(1):1–15
56. Elaziz MA, Mirjalili S (2019) A hyper-heuristic for improving the initial population of whale optimization algorithm. *Knowl Based Syst* 172:42–63
57. Emary E, Zawbaa HM, Sharawi M (2019) Impact of lévy flight on modern meta-heuristic optimizers. *Appl Soft Comput* 75:775–789
58. Oliva D, El Aziz MA, Hassanien AE (2017) Parameter estimation of photovoltaic cells using an improved chaotic whale optimization algorithm. *Appl Energy* 200:141–154
59. Xiong G, Zhang J, Shi D, He Y (2018) Parameter extraction of solar photovoltaic models using an improved whale optimization algorithm. *Energy Convers Manag* 174:388–405
60. Chen H, Xu Y, Wang M, Zhao X (2019) A balanced whale optimization algorithm for constrained engineering design problems. *Appl Math Model* 71:45–59
61. Mafarja MM, Mirjalili S (2017) Hybrid whale optimization algorithm with simulated annealing for feature selection. *Neurocomputing* 260:302–312
62. Abdel-Basset M, El-Shahat D, El-Henawy I, Sangaiah AK, Ahmed SH (2018) A novel whale optimization algorithm for cryptanalysis in Merkle–Hellman cryptosystem. *Mob Netw Appl* 23(4):723–733
63. Jadhav AN, Gomathi N (2018) Wgc: hybridization of exponential grey wolf optimizer with whale optimization for data clustering. *Alex Eng J* 57(3):1569–1584
64. Agrawal R, Kaur B, Sharma S (2020) Quantum based whale optimization algorithm for wrapper feature selection. *Appl Soft Comput* 89:106092
65. Salgotra R, Singh U, Saha S (2019) On some improved versions of whale optimization algorithm. *Arabian J Sci Eng* 44(11):9653–9691
66. Hussien AG, Houssein EH, Hassanien AE (2017) A binary whale optimization algorithm with hyperbolic tangent fitness function for feature selection. In: 2017 Eighth international conference on intelligent computing and information systems (ICICIS). IEEE, pp 166–172
67. Hussien AG, Hassanien AE, Houssein EH, Bhattacharyya S, Amin M (2019) S-shaped binary whale optimization algorithm for feature selection. In: Recent trends in signal and image processing. Springer, pp 79–87
68. Hemasian-Etefagh F, Safi-Esfahani F (2019) Group-based whale optimization algorithm. *Soft Comput* 1–27
69. Hassib EM, El-Desouky AI, Labib LM, El-kenawy E-SM (2019) Woa+ brnn: an imbalanced big data classification framework using whale optimization and deep neural network. *Soft Comput* 1–20
70. Liu M, Yao X, Li Y (2020) Hybrid whale optimization algorithm enhanced with lévy flight and differential evolution for job shop scheduling problems. *Appl Soft Comput* 87:105954
71. Jiang R, Yang M, Wang S, Chao T (2020) An improved whale optimization algorithm with armed force program and strategic adjustment. *Appl Math Model* 81:603–623
72. Guo W, Liu T, Dai F, Xu P (2020) An improved whale optimization algorithm for forecasting water resources demand. *Appl Soft Comput* 86:105925
73. Got A, Moussaoui A, Zouache D (2020) A guided population archive whale optimization algorithm for solving multiobjective optimization problems. *Expert Syst Appl* 141:112972
74. Abdel-Basset M, Manogaran G, El-Shahat D, Mirjalili S (2018) Integrating the whale algorithm with tabu search for quadratic assignment problem: a new approach for locating hospital departments. *Appl Soft Comput* 73:530–546
75. Tharwat A, Moemen YS, Hassanien AE (2017) Classification of toxicity effects of biotransformed hepatic drugs using whale optimized support vector machines. *J Biomed Inform* 68:132–149
76. Zhao D, Liu H, Zheng Y, He Y, Lu D, Lyu C (2019) Whale optimized mixed kernel function of support vector machine for colorectal cancer diagnosis. *J Biomed Inform* 92:103124
77. Gharehchopogh FS, Gholizadeh H (2019) A comprehensive survey: Whale optimization algorithm and its applications. *Swarm Evol Comput* 48:1–24
78. Shahinzadeh H, Gharehpetian GB, Moazzami M, Moradi J, Hosseini SH (2017) Unit commitment in smart grids with wind farms using virus colony search algorithm and considering adopted bidding strategy. In: 2017 Smart Grid Conference (SGC). IEEE, pp 1–9
79. Jayasena KPN, Li L, Elaziz MA, Xiong S (2018) Multi-objective energy efficient resource allocation using virus colony search (vcs) algorithm. In: 2018 IEEE 20th international conference on high performance computing and communications; IEEE 16th international conference on smart city; IEEE 4th international conference on data science and systems (HPCC/SmartCity/DSS). IEEE, pp 766–773
80. Hosseini S, Moradian M, Shahinzadeh H, Ahmadi S (2018) Optimal placement of distributed generators with regard to reliability assessment using virus colony search algorithm. *Int J Renew Energy Res (IJRER)* 8(2):714–723
81. Yousri D, Allam D, Eteiba M (2019) Chaotic whale optimizer variants for parameters estimation of the chaotic behavior in permanent magnet synchronous motor. *Appl Soft Comput* 74:479–503

82. Elaziz MA, Oliva D (2018) Parameter estimation of solar cells diode models by an improved opposition-based whale optimization algorithm. *Energy Convers Manag* 171:1843–1859
83. Elhosseini MA, Haikal AY, Badawy M, Khashan N (2019) Biped robot stability based on an a-c parametric whale optimization algorithm. *J Comput Sci* 31:17–32
84. Tubishat M, Abushariah MA, Idris N, Aljarah I (2019) Improved whale optimization algorithm for feature selection in arabic sentiment analysis. *Appl Intell* 49(5):1688–1707
85. He Y, Dai L, Zhang H (2020) Multi-branch deep residual learning for clustering and beamforming in user-centric network. *IEEE Commun Lett* 24(10):2221–2225. <https://doi.org/10.1109/LCOMM.2020.3005947>
86. Yan J, Meng Y, Yang X, Luo X, Guan X (2021) Privacy-preserving localization for underwater sensor networks via deep reinforcement learning. *IEEE Trans Inform Forensics Secur* 16:1880–1895. <https://doi.org/10.1109/TIFS.2020.3045320>
87. García S, Molina D, Lozano M, Herrera F (2009) A study on the use of non-parametric tests for analyzing the evolutionary algorithms' behaviour: a case study on the cec'2005 special session on real parameter optimization. *J Heuristics* 15(6):617
88. Hussien AG, Oliva D, Houssein EH, Juan AA, Yu X (2020) Binary whale optimization algorithm for dimensionality reduction. *Mathematics* 8(10):1821
89. Mirjalili S, Mirjalili SM, Lewis A (2014) Grey wolf optimizer. *Adv Eng Softw* 69:46–61
90. Hussien AG, Amin M, Abd El Aziz M (2020) A comprehensive review of moth-flame optimisation: variants, hybrids, and applications. *J Exp Theor Artif Intell* 1–21
91. Kaveh A, Talatahari S (2010) An improved ant colony optimization for constrained engineering design problems. *Eng Comput*. <https://doi.org/10.1108/02644401011008577>
92. He Q, Wang L (2007) A hybrid particle swarm optimization with a feasibility-based rule for constrained optimization. *Appl Math Comput* 186(2):1407–1422
93. Gandomi AH, Yang X-S, Alavi AH, Talatahari S (2013) Bat algorithm for constrained optimization tasks. *Neural Comput Appl* 22(6):1239–1255
94. Hussien AG (2021) An enhanced opposition-based salp swarm algorithm for global optimization and engineering problems. *J Ambient Intell Humaniz Comput* 1–22
95. Liu Y, Zhang Z, Liu X, Wang L, Xia X (2021) Efficient image segmentation based on deep learning for mineral image classification. *Adv Powder Technol* 32(10):3885–3903
96. Liu Y, Zhang Z, Liu X, Wang L, Xia X (2021) Ore image classification based on small deep learning model: Evaluation and optimization of model depth, model structure and data size. *Miner Eng* 172:107020. <https://doi.org/10.1016/j.mineng.2021.107020>
97. Otsu N (1979) A threshold selection method from gray-level histograms. *IEEE Trans Syst Man Cybern* 9(1):62–66
98. Kapur JN, Sahoo PK, Wong AK (1985) A new method for gray-level picture thresholding using the entropy of the histogram. *Comput Vis Graph Image Process* 29(3):273–285
99. Huynh-Thu Q, Ghanbari M (2008) Scope of validity of psnr in image/video quality assessment. *Electron Lett* 44(13):800–801
100. Wang Z, Bovik AC, Sheikh HR, Simoncelli EP (2004) Image quality assessment: from error visibility to structural similarity. *IEEE Trans Image Process* 13(4):600–612
101. Zhang L, Zhang L, Mou X, Zhang D (2011) Fsim: a feature similarity index for image quality assessment. *IEEE Trans Image Process* 20(8):2378–2386
102. Qiu S, Wang Z, Zhao H, Hu H (2016) Using distributed wearable sensors to measure and evaluate human lower limb motions. *IEEE Tran Instrum Meas* 65(4):939–950
103. Yang C, Zhao H, Bruzzone L, Benediktsson JA, Liang Y, Liu B, Zeng X, Guan R, Li C, Ouyang Z (2020) Lunar impact crater identification and age estimation with Chang'e data by deep and transfer learning. *Nat Commun* 11(1):6358. <https://doi.org/10.1038/s41467-020-20215-y>
104. Li J, Chen C, Chen H, Tong C (2017) Towards context-aware social recommendation via individual trust. *Knowl Based Syst* 127:58–66. <https://doi.org/10.1016/j.knsys.2017.02.032>
105. Li J, Lin J (2020) A probability distribution detection based hybrid ensemble qos prediction approach. *Inf Sci* 519:289–305. <https://doi.org/10.1016/j.ins.2020.01.046>
106. Li J, Zheng X-L, Chen S-T, Song W-W, Chen D-R (2014) An efficient and reliable approach for quality-of-service-aware service composition. *Inf Sci* 269:238–254. <https://doi.org/10.1016/j.ins.2013.12.015>
107. Jin L, Wen Z, Hu Z (2020) Topology-preserving nonlinear shape registration on the shape manifold. *Multimed Tools Appl* 1–13
108. Wu X, Xu X, Liu J, Wang H, Hu B, Nie FJ (2020) Supervised feature selection with orthogonal regression and feature weighting. *IEEE Trans Neural Netw Learn Syst*. <https://doi.org/10.1109/TNNLS.2020.2991336>
109. Deng W, Xu J, Zhao H, Song Y (2020) A novel gate resource allocation method using improved pso-based qea. *IEEE Trans Intell Transp Syst*. <https://doi.org/10.1109/TITS.2020.3025796>
110. W D, JJ X, YJ S, HM Z (2020) An effective improved co-evolution ant colony optimization algorithm with multi-strategies and its application. *Int J Bioinspired Comput* 16(3):158–170
111. Wang X, Bennamoun M, Sohel F, Lei H (2021) Diffusion geometry derived keypoints and local descriptors for 3d deformable shape analysis. *J Circuits Syst Comput* 30(01):2150016
112. Wang X, Sohel F, Bennamoun M, Guo Y, Lei H (2017) Scale space clustering evolution for salient region detection on 3d deformable shapes. *Pattern Recognit* 71:414–427
113. Feng C, Zhu Z, Cui Z, Ushakov V, Dreher J, Luo W, Gu R, Wu X, Krueger F (2021) Prediction of trust propensity from intrinsic brain morphology and functional connectome. *Hum Brain Mapp* 42(1):175–191
114. Li Q, Wu X, Liu T (2021) Differentiable neural architecture search for optimal spatial/temporal brain function network decomposition. *Med Image Anal* 69:101974. <https://doi.org/10.1016/j.media.2021.101974>
115. Zhang L, Zhang Z, Wang W, Jin Z, Su Y, Chen H (2021) Research on a covert communication model realized by using smart contracts in blockchain environment. *IEEE Syst J*. <https://doi.org/10.1109/JSYST.2021.3057333>
116. Zhang L, Zhang Z, Wang W, Waqas R, Zhao C, Kim S, Chen H (2020) A covert communication method using special bitcoin addresses generated by vanitygen. *Comput Mater Continua* 65(1):597–616 <http://www.techscience.com/cmcc/v65n1/39585>
117. Zhang L, Zou Y, Wang W, Jin Z, Su Y, Chen H (2021) Resource allocation and trust computing for blockchain-enabled edge computing system. *Comput Secur*. <https://doi.org/10.1016/j.cose.2021.102249>
118. Chen H, Yang B, Liu J, Zhou X-N, Philip SY (2019) Mining spatiotemporal diffusion network: a new framework of active surveillance planning. *IEEE Access* 7:108458–108473
119. Luo J, Li M, Liu X, Tian W, Zhong S,... Shi K (2020) Stabilization analysis for fuzzy systems with a switched sampled-data control. *J Franklin Inst* 357(1):39–58. <https://doi.org/10.1016/j.jfranklin.2019.09.029>
120. Liu X, Yang B, Chen H, Musial K, Chen H, Li Y, Zuo W (2021) A scalable redefined stochastic blockmodel. *ACM Trans Knowl Discov Data (TKDD)* 15(3):1–28
121. Cao X, Cao T, Gao F, Guan X (2021) Risk-averse storage planning for improving res hosting capacity under uncertain siting choice. *IEEE Trans Sustain Energy*. <https://doi.org/10.1109/TSTE.2021.3075615>

122. Fei X, Wang J, Ying S, Hu Z, Shi J (2020) Projective parameter transfer based sparse multiple empirical kernel learning machine for diagnosis of brain disease. *Neurocomputing* 413:271–283. <https://doi.org/10.1016/j.neucom.2020.07.008>
123. Hu Z, Wang J, Zhang C, Luo Z, Luo X, Xiao L, Shi J, Uncertainty modeling for multi center autism spectrum disorder classification using takagi-sugeno-kang fuzzy systems. *IEEE Trans Cogn Dev Syst*
124. Saber A, Sakr M, Abo-Seida OM, Keshk A, Chen H (2021) A novel deep-learning model for automatic detection and classification of breast cancer using the transfer-learning technique. *IEEE Access* 9:71194–71209. <https://doi.org/10.1109/ACCESS.2021.3079204>
125. Qiu S, Wang Z, Zhao H, Qin K, Li Z, Hu H (2018) Inertial/magnetic sensors based pedestrian dead reckoning by means of multi-sensor fusion. *Inf Fusion* 39:108–119
126. Huang P, Zhao L, Jiang R, Wang T, Zhang X (2021) Self-filtering image dehazing with self-supporting module. *Neurocomputing* 432:57–69
127. Wang T, Zhao L, Huang P, Zhang X, Xu J (2021) Haze concentration adaptive network for image dehazing. *Neurocomputing* 439:75–85
128. Zhang X, Wang T, Wang J, Tang G, Zhao L (2020) Pyramid channel-based feature attention network for image dehazing. *Comput Vis Image Underst* 197–198:103003. <https://doi.org/10.1016/j.cviu.2020.103003>
129. Zhou W, Yu L, Zhou Y, Qiu W, Wu M, ... Luo T (2018) Local and Global Feature Learning for Blind Quality Evaluation of Screen Content and Natural Scene Images. *IEEE Trans Image Process* 27(5):2086–2095. <https://doi.org/10.1109/TIP.2018.2794207>
130. Zhang X, Fan M, Wang D, Zhou P, Tao D Top-k feature selection framework using robust 0-1 integer programming. *IEEE Trans Neural Netw Learn Syst*
131. Zhang X, Li W, Ye X, Maybank S (2015) Robust hand tracking via novel multi-cue integration. *Neurocomputing* 157:296–305

**Publisher's Note** Springer Nature remains neutral with regard to jurisdictional claims in published maps and institutional affiliations.