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New binary archimedes optimization algorithm and its application

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A R T I C L E I N F O

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A B S T R A C T

Optimization problem, as a hot research field, is applied to many industries in the real world. Due to the complexity of different search spaces, metaheuristic optimization algorithms are proposed to solve this problem. As a recently introduced optimization method inspired by physics, Archimedes Optimization Algorithm (AOA) is an efficient metaheuristic algorithm based on Archimedes' law. It has the advantages of fast convergence speed and balance between local and global search ability when solving continuous problems. However, discrete problems exist more in practical applications. AOA needs to be further improved in dealing with such problems. On this basis, to make Archimedes Optimization Algorithm better applied to solve discrete problems, a Binary Archimedes Optimization Algorithm (BAOA) is proposed in this paper, which incorporates a novel V-shaped transfer function. The proposed method applies the BAOA to COVID-19 classification of medical data, segmentation of real brain lesion, and the knapsack problem. The experimental results show that the proposed BAOA can solve the discrete problem well.

1. Introduction

As a common method to solve global optimization problems, metaheuristic optimization algorithms have been widely used in automation, mechanical engineering, and other projects in recent years. It is a flexible and gradient-blind method, which can be mainly divided into four categories: evolutionary algorithms based on the simulation of survival of the fittest in nature, such as Tree Growth Algorithm (TGA) (Armin Cheraghalipour et al., 2018); swarm intelligence algorithms based on simulated swarm behavior, such as Giant Trevally Optimizer (GTO) (Haval Tariq Sadeeq and Adnan Mohsin Abdulazeez, 2022) and Dwarf Mongoose Optimization Algorithm (DMO) (Jeffrey O. Agushaka et al., 2022); human-based-algorithms based on simulation of human behavior, such as Group Teaching Optimization Algorithm (GTOA) (Zhang and Jin, 2020) and Queuing Search (QS) (Jinhao Zhang et al., 2018); science-based-algorithms based on physical rules and chemical reactions in the universe, such as Atomic Orbital Search (AOS) (Mahdi Azizi, 2021) and Crystal Structure Algorithm (CryStAl) (Talatahari et al., 2021). At present, most of the proposed metaheuristic optimization algorithms have different performances in solving problems due to the different phenomena simulated, so they are especially effective for a particular problem. For example, the Grasshopper Optimization Algorithm (GOA) proposed by Saremi et al. (2017) and the Particle Swarm Optimization Algorithm (PSO) proposed by Eberhart and Kennedy (1995) have a simple structure, strong stability, few parameters, and fast convergence speed, which are often applied to feature selection. The whale Optimization Algorithm (WOA) proposed by Mirjalili and Lewis (2016) and the Artificial Bee Colony algorithm (ABC) proposed by Karaboga and Basturk (2007) have a simple mechanism, few parameters, and strong optimization ability, which are often applied to image segmentation. However, the above algorithms can solve specific cases and do not have generality. Therefore, a metaheuristic optimization algorithm that can optimally solve more general problems and obtain stable results is urgently needed.

Archimedes Optimization Algorithm (AOA) is an optimization algorithm based on the physical laws of Archimedes principle proposed by Fatma A. Hashim et al. (2020). It calculates the optimal solution based on the phenomenon that an object can reach equilibrium after a series of collisions in the fluid. It's a swarm intelligence algorithm. AOA can maintain the balance between the global and local search ability, and the accuracy is relatively high, so it is suitable for solving a variety of complex continuous problems.

Besides, feature selection is an important preprocessing method in machine learning and data mining. Commonly used feature selection methods can be divided into similarity-based, information-theoretical-based, sparse-learning-based, and statistical-based methods (Li et al., 2017). Feature selection maintains the physical meaning of the original features, making the model more readable and interpretable, which has

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been widely used in image processing, natural language processing, and so on. Image segmentation technology is the basis of computer vision and an important part of image understanding. Because of its importance and difficulty, the image segmentation problem has attracted many researchers to pay great efforts since the 1970 s. The common image segmentation techniques include the traditional methods based on topology (Yamina Yahia Lahssene et al., 2021), threshold (Yi Chen et al., 2022), U-net, Nabla-net, and other efficient networks (Guota Wang et al., 2018). The 0–1 knapsack problem is popular in exploiting resources optimally to maximize profit and minimize cost, which often occurs in such problems as an investment decision, main budgeting, resource allocation, etc. (Mohamed Abdel-Basset et al., 2021). Therefore, whether the algorithm can effectively solve the 0–1 knapsack problem can reflect the performance of the model to a certain extent.

Since most metaheuristic optimization algorithms are designed to solve continuous problems, they are mainly applied in the field of continuous optimization and are not suitable for solving discrete problems. To solve the problem, the continuous search space is need to be mapped to the binary domain by adding a transfer function. After the transfer function transformation, the metaheuristic optimization algorithm can be applied to solve discrete problems. To give full play to the advantages of AOA, this paper proposes a new Binary Archimedes Optimization Algorithm (BAOA) combined with a novel V-shaped transfer function and applies it to feature selection, image segmentation, and 0–1 knapsack. To apply BAOA to specific fields, this paper obtains clinical patient data from the Kaggle Challenge database and the Second Affiliated Hospital of Dalian Medical University for the classification of medical data and the segmentation of medical image. Besides, four groups of different sizes of knapsack data are used to further verify the availability and performance of the proposed BAOA. The main contributions of this paper are as follows:

A new binary variant of AOA is proposed, called BAOA, which incorporates a novel V-shaped transfer function in this paper.

Based on improved fitness functions, the proposed BAOA can be applied to select the optimal feature subset for data classification, segment images, and tackle 0–1 knapsack problem.

To verify that the BAOA algorithm can be suitable for specific fields, the proposed method cooperates with the clinical data and medical images from Kaggle Challenge database and Second Affiliated Hospital of Dalian Medical University, respectively.

This paper is divided into six sections. The first section mainly introduces the relevant research background of the paper. The second section mainly introduces the research status and related applications of binary heuristic optimization algorithms. The third section mainly introduces the AOA and the new V-shape transfer function proposed in this paper and the implementation process of BAOA obtained by their fusion. The fourth section mainly describes the experimental methods and implementation process of applying BAOA in the classification of medical data, segmentation of medical image, and knapsack problem. The fifth section mainly shows the experimental results and related evaluation indicators of the above three groups of experiments. The sixth section provides conclusions.

2. Related work

2.1. The existing BAOA methods

As a kind of efficient metaheuristic optimization algorithm, AOA has been proposed in a variety of binary variants and applied to discrete problems. Ahmet Cevahir CINAR integrates 17 commonly used transfer functions into AOA and proposed 17 binary variants of AOA for solving the uncapacitated facility location problem (UFLP) (Ahmet Cevahir Cinar, 2022), and the used transfer functions are shown in Table 1.

In Table 1, c means the continuous value, tv means transferred value, e means exponential function, tanh is hyperbolic tangent function, atan is inverse tangent in radians, erf is error function, *failure* is the number of failures, $Q\max$ and $Q\min$ are predetermined values for non-stationary transfer functions, *Max_iter* is the maximum number of iteration, *iter* is the current iteration number, sin is the sinus function, cos is the cosinus function, *mod* is the modulo function, *round* is the round function, *abs* is the absolute value function, and *fix* is the round towards zero function.

Table 1
The mathematical formulas of 17 transfer functions.

Name	Formula
TF1	$tv = \frac{1}{(1+e^{-c})}$
TF2	$tv = \frac{1}{(1+e^{-2c})}$
TF3	$tv = \frac{1}{(1+e^{\frac{-c}{2}})}$
TF4	$tv = abs(\tanh(2c))$
TF5	$tv = abs(\frac{2}{\pi} \times \mathrm{atan}(\frac{\pi}{2} \times c))$
TF6	$tv = (\mathrm{erf}(\frac{\sqrt{\pi}}{2} \times c))$
TF7	$tv = \mathrm{erf}(\frac{failure}{Max\_iter}) + 1 - \mathrm{erf}(\frac{failure}{Max\_iter}) \times abs(\tanh(c))$
TF8	$tv = abs(\frac{c}{\sqrt{1+c^2}})$
TF9	$tv = \frac{1}{(1+e^{\frac{-c}{Q\max - iter \times ((Q\max - Q\min)/Max\_iter)}})}$
TF10	$tv = \frac{1}{(1+e^{\frac{-c}{Q\max - iter \times ((Q\max - Q\min)/Max\_iter)}})}$
TF11	$tv = \begin{cases} 1 - \frac{2}{1+e^{\frac{-2c}{Q\max - iter \times ((Q\max - Q\min)/Max\_iter)}}}, & x \leqslant 0 \\ \frac{2}{1+e^{\frac{-2c}{Q\max - iter \times ((Q\max - Q\min)/Max\_iter)}}} - 1, & x > 0 \end{cases}$
TF12	$tv = \begin{cases} 1 - \frac{2}{1+e^{\frac{-c}{2 \times (Q\max - iter \times ((Q\max - Q\min)/Max\_iter))}}}, & x \leqslant 0 \\ \frac{2}{1+e^{\frac{-c}{2 \times (Q\max - iter \times ((Q\max - Q\min)/Max\_iter))}}} - 1, & x > 0 \end{cases}$
TF13	$tv = (c - (-10))/(20)$
TF14	$tv = abs(\tanh(c))$
TF15	$tv = abs(\sin(2 \times \pi \times c \times \cos(2 \times \pi \times c)))$
TF16	$tv = \bmod(round(abs(\bmod(c,2))),2)$
TF17	$tv = fix(abs(\bmod(x,2)))$

In this paper, the first binarization process for AOA is conducted with 17 transfer functions. Peculiar parameter analyses for binary optimization problems are performed in the best variant (BAOA9) produced with the TF9 transfer function. Ahmet's research confirms that BAOA has a good effect in solving the discrete problem of UFLPs, but the application of BAOA in solving other discrete problems is not discussed.

2.2. Other binary metaheuristic optimization algorithms

Due to the superiority of metaheuristic optimization algorithms over conventional optimization algorithms (Cheng & Prayogo, 2014), a large number of binary metaheuristic optimization algorithms have been proposed to solve discrete problems.

For feature selection, Binary Chimp Optimization Algorithm (BChOA) proposed by Jianhao Wang et al. (2021) can effectively implement feature selection in biomedical data classification. Besides, the method verifies that the slope of the transfer function can significantly affect the performance of the model. Binary Fish Migration Optimization Algorithm (ABFMO) proposed by J.S. Pan et al. (2021), Binary Symbiotic Organism Search Algorithm (IBSOS) proposed by Z.G. Du et al. (2020), and Binary Butterfly Optimization Approaches (bBOA) proposed by Aroraa and Anandb (2019) also solve the feature selection problem. For image segmentation, the New Ensemble Multi-swarm method based on Teaching-learning-based Optimization (EMTLBO) proposed by Ziqi Jiang et al. (2022) optimize the image threshold segmentation. Multi-leader Whale Optimization Algorithm (MLWOA) proposed by Mohamed Abd Elaziz et al. (2021) is applied to determine the optimal threshold, which uses the Otsu method, fuzzy entropy, and Kapur's entropy as a fitness function. For 0–1 knapsack problem, Binary Marine Predators Algorithm (BMPA) proposed by Mohamed Abdel-Basset et al. (2021) conclude that the performance of binary algorithm depends on proper selection of transfer function. Cohort Intelligence (CI) proposed by Kulkarni and Shabir (2016) can solve 0–1 knapsack problem on a small dataset of 75 dimensions.

Additionally, the No-Free-Lunch theorem attests that there is no single optimization algorithm that is adequate to provide a solution for all optimization algorithms (Mafarja & Mirjalili, 2017). On this basis, this paper hopes to make full use of the advantages of AOA, so that it can be used to solve as many discrete problems as possible.

3. Archimedes optimization algorithm

3.1. Mathematical principle of archimedes optimization algorithm (AOA)

Archimedes Optimization Algorithm is a metaheuristic algorithm, which analyzes the phenomenon that an object immersed in a fluid will experience an upward buoyant force equal to the weight of the fluid displaced by the object. It further infers that the buoyancy force on an object in a fluid is related to the physical density, volume, and acceleration of the object in motion. When a certain point reaches, the net force on the body in the fluid is zero and the body is in equilibrium, as shown in Fig. 1.

The concrete mathematical model of the AOA is established as follows:

Firstly, a state transition operator *TF* is proposed to describe the transition from global to local search of an object in a fluid:

$$TF = \exp\left(\frac{t - t_{\max}}{t_{\max}}\right) \tag{1}$$

where t represents the current number of iterations, $t_{\max}$ represents the maximum number of iterations. Here, $TF = 1$ indicates that the object has reached an equilibrium state.

Secondly, a density factor d at the next number of iterations $t+1$ is proposed to better describe the transition of objects from global to local search, which is defined as follows:

$$d^{t+1} = \exp\left(\frac{t_{\max} - t}{t_{\max}}\right) - \frac{t}{t_{\max}} \tag{2}$$

when $d = 0$, the object is in equilibrium.

Finally, to describe the collision between physical objects, the acceleration factor acc_i^{t+1} of the object i is defined as follows:

$$acc_i^{t+1} = \begin{cases} \dfrac{den_{mr} + vol_{mr} \times acc_{mr}}{den_i^{t+1} \times vol_i^{t+1}} & TF \leqslant 0.5 \\ \dfrac{den_{best} + vol_{best} \times acc_{best}}{den_i^{t+1} \times vol_i^{t+1}} & TF > 0.5 \end{cases} \tag{3}$$

where acc_i^{t+1} , den_i^{t+1} and vol_i^{t+1} represent the acceleration, density, and volume of the object at time t, respectively; acc_{mr} , den_{mr} and vol_{mr} represent the acceleration, density, and volume of the random object, respectively; acc_{best} , den_{best}, and vol_{best} represent the acceleration, density, and volume of the optimal object, respectively.

Here, the acceleration factor *acc* changes in two processes: when $TF \leqslant 0.5$, there is a collision between objects and the update of acceleration is related to the determinant of random objects. When $TF > 0.5$, there is no collision between objects and the update of acceleration is related to the determinants of the current best object. The corresponding acceleration factor is normalized as follows:

$$acc_{i-norm}^{t+1} = u \times \frac{acc_i^{t+1} - \min(acc)}{\max(acc) - \min(acc)} + k \tag{4}$$

where u and k are constants.

In the whole process, the object changes its position based on two stages according to the change of acceleration (equation (3):

$$x_i^{t+1} = \begin{cases} x_i^t + c_1 \times rand \times acc_{i-norm}^{t+1} \times d \times (x_{rand} - x_i^t) \quad TF \leqslant 0.5 \\ \begin{cases} x_{best}^t + c_2 \times rand \times acc_{i-norm}^{t+1} \times d \times (T \times x_{best} - x_i^t) & P < 0.5 \\ x_{best}^t - c_2 \times rand \times acc_{i-norm}^{t+1} \times d \times (T \times x_{best} - x_i^t) & P \geqslant 0.5 \end{cases} \quad TF > 0.5 \end{cases} \tag{5}$$

where $rand$ is a uniform random number between 0 and 1, $T = c_3 \times TF$, $P = 2 \times rand - c_4$, c_1, c_2, c_3 and c_4 are constants, x_i^{t+1} ,x_{rand} and x_{best} represent the position of the object i at time $t + 1$, the position of the random object, and the position of the best object, respectively.

3.2. Process of archimedes optimization algorithm

Step 1: Initialize the position, density, volume, acceleration, and other parameters of the object.

Step 2: Start the iteration and update the transition operator *TF* and density factor d by equations (1) and (2).

Step 3: Judge the size bits of *TF* and update the density, volume, acceleration, and position of each object according to equations (3), (4), and (5), respectively.

Step 4: Calculate the fitness value of the object.

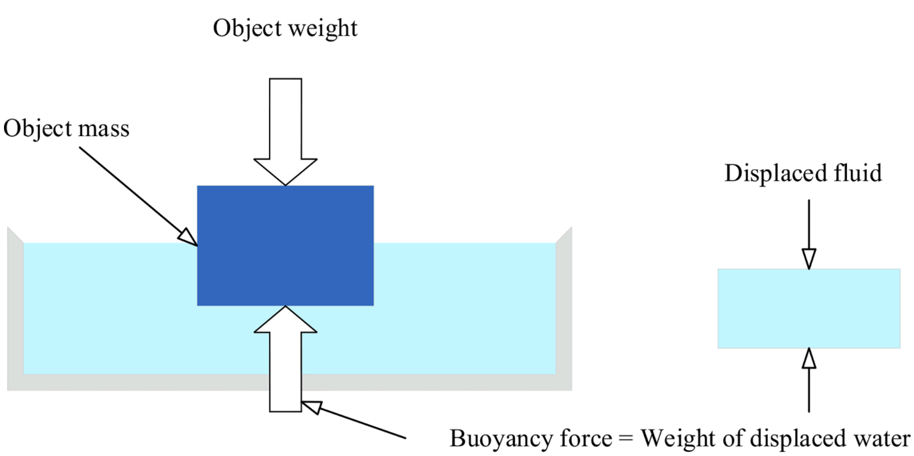


Fig. 1. Diagram of forces acting on an object in a liquid.

Step 5: Update the fitness value of the object. If the current fitness value is less than the optimal value, the current value will be taken as the optimum. Besides, the object corresponding to the current fitness value is updated to the optimal position.

Step 6: Judge the size of the iteration number t. If it is less than the maximum iteration number, return to Step 2 and repeat the subsequent operations otherwise output the optimal fitness value and its corresponding position.

Pseudo code of AOA

```
Initialize the constant factors c1 ,c2, c3, c4, the number of objects n, and the maximum
   number of iterations Max_iter.
   Initialize object population with the random position Xi(i = 1, 2, ..., n).
   Evaluate the initial population and select the population with the best fitness value.
   Set the iteration counter t = 1.
   while t < max_iter do
   TF and d are updated according to equations (2)–(1) and (2–2)
   if TF⩽0.5
   Update acc_norm using equations (3), (4) and (5)
   end if
   if TF > 0.5
   Update acc_norm using equations (3), (4) and (5)
   end if
   Calculate the fitness value of each object
   Select the better position and update the corresponding Xbest, den_best, vol_best and
   acc_best
   t = t + 1
   end while
   return Xbest
```

The AOA has a strong ability to balance the global and the local search ability, which is less affected by the number of adaptive parameters. However, as a population-based optimization algorithm, AOA is prone to fall into the local optimal solution due to the decline of population diversity in the late iteration, which may result in slow convergence of the algorithm.

4. The proposed method

Since AOA has been applied to practical problems such as microgrid operation planning (Nguyen et al., 2022), wind speed forecasting (Zhang et al., 2021), and bearing fault diagnosis (Wang et al. 2022), which verifies that AOA can solve continuous problems well and be applied into multiple fields in the real world. Because AOA is designed to solve continuous problems, it cannot be directly used to deal with discrete problems. This paper aims at solving discrete problems efficiently by a novel binary variant of AOA combined with a novel V-shaped transfer function, which can greatly improve the exploration ability by transforming the continuous search space into a binary search space.

4.1. The proposed V-shaped binary archimedes optimization algorithm

To make AOA suitable for discrete problems, a transfer function is needed to map the continuous search space to the discrete space. The transfer function discretizes the algorithm by evaluating the values of different solutions in different dimensions. The V-shaped transfer function is a classical transfer function, which can transform the algorithm from continuous to discrete without modifying the overall structure of the algorithm. The classical expressions of V-shaped transfer functions are shown in equations (6) and (7):

$$t_1(x) = |\arctan(x)| \tag{6}$$

$$t_2(x) = \left|\frac{x}{\sqrt{1+x^2}}\right| \tag{7}$$

Among them, x is the initial position of the object. Considering that the transfer function is used to transform the continuous search space into a binary domain, the change of function value of the transfer function should be between 0 and 1.

Definition 1. *the proposed V-shaped transfer function.*

Because the common V-shaped transfer function changes too drastically in the interval [-5,5], which will affect the performance of the algorithm, this paper proposes t_3 function as follows:

$$t_3(x) = \left|\arctan(x) \times \frac{x}{\sqrt{1+x^2}}\right| \tag{8}$$

The comparison of the proposed transfer function t_3 with the classical t_1 and t_2 is shown in Fig. 2.

Definition 2. *the proposed V-shaped function incorporating a scaling coefficient a.*

$$t_3(x) = \alpha \times \left|\arctan(x) \times \frac{x}{\sqrt{1+x^2}}\right| \tag{9}$$

To make the value of the proposed V-shaped function lie between 0 and 1, the limit should meet the following:

$$\lim_{x\to\infty} \alpha \times \left|\arctan(x) \times \frac{x}{\sqrt{1+x^2}}\right| \leqslant 1$$

It's not hard to figure out that when the limit on the left-hand side of this inequality is equal to 1, the value of a is $\frac{2}{\pi}$. To satisfy the above constraint condition, the scaling coefficient a should be less than 0.64.

Definition 3. *performance criterion of function t_3 using different scaling coefficient a* ($a\leqslant0.64$).

To evaluate the global and local search ability of the proposed algorithm using the proposed V-shaped transfer function t_3, the performance criterion is introduced as follows (Zhang et al., 2020):

$$L = \frac{\sum_{i=1}^{n} x_i^t \oplus x_{best}}{n} \tag{10}$$

where L represents the value of the average distance of all objects to the global optimal value, $\oplus$ represents the XOR operation of the current and the optimal positions in each dimension, and n represents the number of objects. The larger L is, the stronger the global search ability will be, and otherwise, the stronger the local search ability will be.

Case: In this paper, the transfer function t_3 with different scaling coefficients is applied to BAOA to calculate and compare the value of L. To fully consider the effect of different scaling coefficients on the algorithm, a is taken as 0.08, 0.24, 0.40, and 0.64, respectively. This paper uses two datasets as shown in Table 2 to conduct experiments. Because

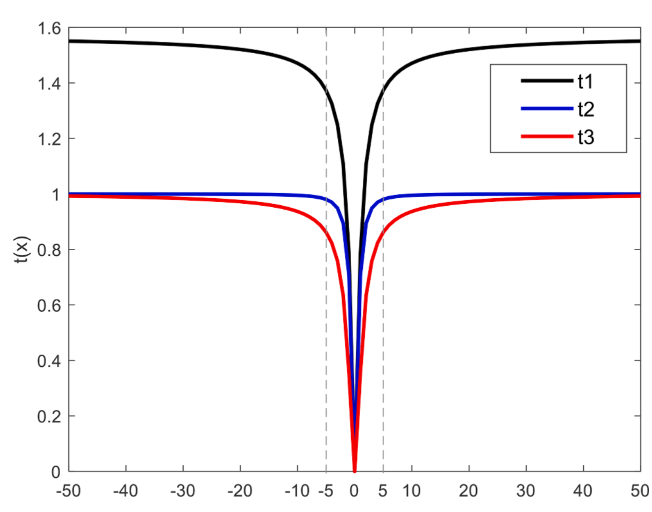


Fig. 2. Comparison of different V-shaped transfer functions.

Table 2
Basic Information of Datasets.

The dataset	Number of instances	Number of features	Number of categories
Cancer	683	9	2
Heartdata	270	13	2

the value does not change significantly after the number of iterations exceeds 20, the corresponding iteration value is evaluated 20 times in this experiment.

It can be seen from Fig. 3 that when $a = 0.64$, the average value of the performance criterion L is the largest, which means that when $a = 0.64$, the function t_3 has a strong global search ability. Thus, the scaling coefficient a of the proposed V-shaped transfer function t_3 used in this paper is 0.64.

Combining equation (5) and equation (9), the position update of BAOA can be obtained as follows:

$$X_i^{t+1} = \begin{cases} 1 & rand < t_3(x_i^t) \\ 0 & rand \geqslant t_3(x_i^t) \end{cases} \tag{11}$$

where X_i^{t+1} represent the position of the object i at a time $t+1$. Compared with the classical AOA, the proposed V-Shaped BAOA avoids the problem that the performance of the algorithm is affected by different original positions of objects.

4.2. The implementation process of the proposed BAOA

By combining with the proposed transfer function, the implementation of the proposed BAOA is shown in Fig. 4.

The proposed method can reduce the influence of the initial position and effectively solve the discrete problems. The concrete process is as follows:

Step 1: Initialize the constant factor of objects, the number of objects, and the maximum number of iterations.

Step 2: Initialize randomly the initial position of the object.

Step 3: Use the fitness function to evaluate the position of each individual.

Step 4: Find the optimal position and the corresponding optimal concentration, volume, and acceleration.

Step 5: Update *TF*, *d*, and *acc* according to equations (1), (2), and (3), respectively.

Step 6: Judge the value range of *TF* and update the acceleration and position of each object according to equations (4) and (5).

Step 7: Update the optimal position of the object.

Step 8: Change position to discrete space.

Step 9: Judge the size of the number of iterations t. If it is less than the maximum number of iterations, return to the fifth step; otherwise, end the iteration and output the optimal position.

The corresponding pseudo code is shown as follows:

Pseudo code of BAOA

Initialize the constant factors c_3, c_4, the number of objects n, and the maximum number of iterations *Max_iter*.
Randomize the initial position of the object $X_i (i = 1, 2, ..., n)$.
Evaluate the position of each individual by the fitness function.
Find the optimal position *Xbest*, the corresponding optimal concentration *den_best*, optimal volume *vol_best*, and optimal acceleration *acc_best*.
while $t < Max\_iter$ do
Update *TF*, *d*, and *acc* according to equations (1), (2), and (3), respectively.
for each object do
if $TF \leqslant 0.5$
Update *acc_norm* using equations (3), (4), and (5)
end if
if $TF > 0.5$
Update *acc_norm* using equations (3), (4), and (5)
end if
end for
If a better location is found, *Xbest* is updated, along with its corresponding *den_bestvol_best*, and *acc_best*
Call the transfer function V
$t = t + 1$
end while
return *Xbest*

4.3. Application of the proposed method

After integrating the novel V-shaped transfer function, the proposed BAOA can well solve discrete problems: clinical medical data processing and theoretical data dichotomization, i.e., COVID-19 classification, brain lesion segmentation, and 0–1 knapsack problem.

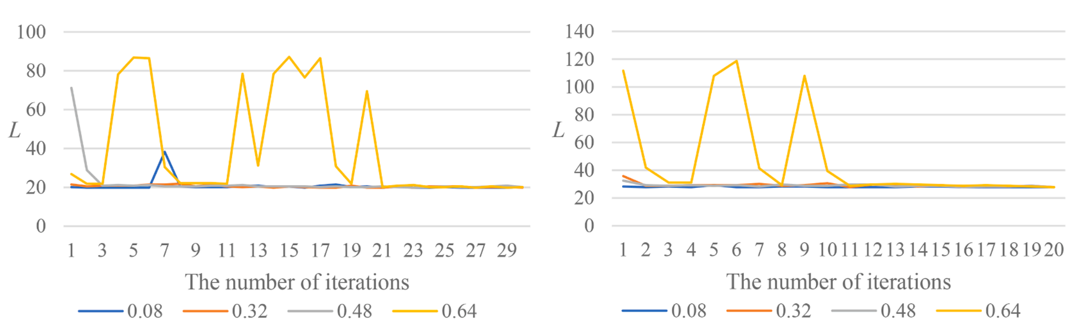
4.3.1. COVID-19 classification of medical data

Nowadays, how to defeat or reasonably control the development of COVID-19 is a worldwide problem facing people all over the world. At present, the key lies in the early detection and control of the source of infection. In this paper, BAOA is applied in the COVID-19 classification through the symptoms of the patient, which can play an auxiliary role in early COVID-19 detection. Assuming that COVID-19 datasets contain n features, 2^n permutations will be generated according to the principle of combination. For each feature in the datasets, there will be a choice to add it to the feature subset or not. The selected and unselected features are 1 and 0 in the tag array, respectively.

To weigh the influence of classification accuracy and feature number, the fitness function of COVID-19 classification (Mafarja and Mirjalili, 2018) is as follows:

$$fitness_{COV} = \alpha \cdot \gamma(D) + \beta \cdot \frac{|R|}{|N|} \tag{12}$$

where $\gamma(D)$ represents the classification accuracy obtained from the input feature subset, $|R|$ represents the number of elements in the feature subset, $|N|$ represents the number of elements in the feature set, α and β



(a) Cancer (b) Heartdata

Fig. 3. Comparison of performance criterion L with different scaling coefficients a.

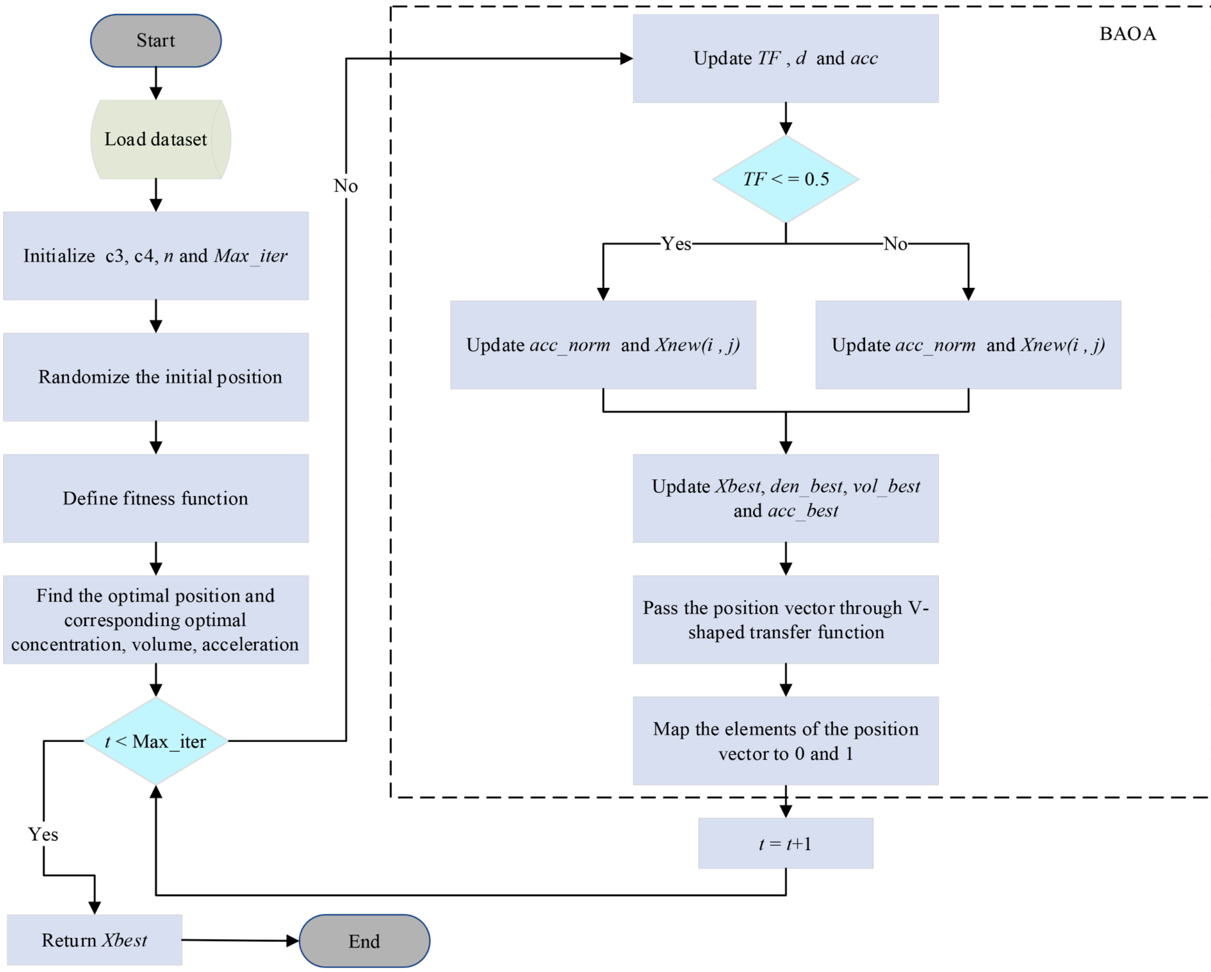


Fig. 4. The flow chart of BAOA.

are the adjustment coefficients, in this paper, $\alpha \in [0,1] h\beta = 1 - \alpha$ are adopted from (Emary et al., 2016a).

4.3.2. Segmentation of clinical brain lesion

As one of the most important organs of the human body, the brain is the highest part of the central nervous system, which is in charge of the physiological functions of people. In the treatment stage, accurate segmentation of brain lesion from medical images has an important auxiliary role. In this paper, the maximum entropy principle (Kapur et al., 1985) is combined with BAOA to solve the segmentation problem of clinical brain lesion. The specific implementation process is as follows:

$$H_0(x) = -\sum_{0 \leqslant k \leqslant x} \frac{p(k)}{\alpha_0(x)} \log \frac{p(k)}{\alpha_0(x)} \tag{13}$$

$$H_1(x) = -\sum_{x < k \leqslant M} \frac{p(k)}{\beta_0(x)} \log \frac{p(k)}{\beta_0(x)} \tag{14}$$

$$H = H_0(x) + H_1(x) \tag{15}$$

where M is obtained by subtracting 1 from the number of discrete data sources and x is a specific threshold whose size is between 0 and M. $H_0(x)$, $H_1(x)$, H, $p(k)$, $\alpha_0(x)$, and represents the healthy tissue entropy, the brain lesion entropy, the total entropy, the estimated probability distribution function, the cumulative probability of healthy tissue pixels, the cumulative probability of brain lesion pixels, respectively.

The basic principle is to obtain the total entropy by calculating the entropy of the brain lesion part and the healthy tissue part. When the total entropy reaches the maximum, the corresponding threshold is optimum. The larger the total entropy is, the more information is retained when the image is segmented with the threshold. Based on this feature of the maximum entropy principle, the fitness function of the proposed method is obtained as follows:

$$fitness_{IMA} = H = H_0(x) + H_1(x) \tag{16}$$

4.3.3. The knapsack problem

0–1 knapsack problem can be described as: there is a backpack with a capacity of c and n items, each with a corresponding weight w and value v. Each item can only be packed into the backpack or not, so that the total value of the items in the backpack can obtain the maximum. Besides, the total weights of selected items must be less than or equal to the capacity of the knapsack. In this paper, the fitness function of 0–1 knapsack problem is adopted as:

$$fitness_{KNA} = \sum_{i=1}^{n} v_i x_i \tag{17}$$

where v_i represents the value of the ith item, and x_i represents the corresponding decision on the ith item, whose value is 0 or 1.

4.3.4. The process of experiments

The implementation process of applying BAOA to the above three kinds of experiments is divided into the following six steps and the corresponding flow chart is shown in Fig. 5.

Step 1: According to different experiments, load the corresponding COVID-19 data, clinical image, and knapsack data, respectively.

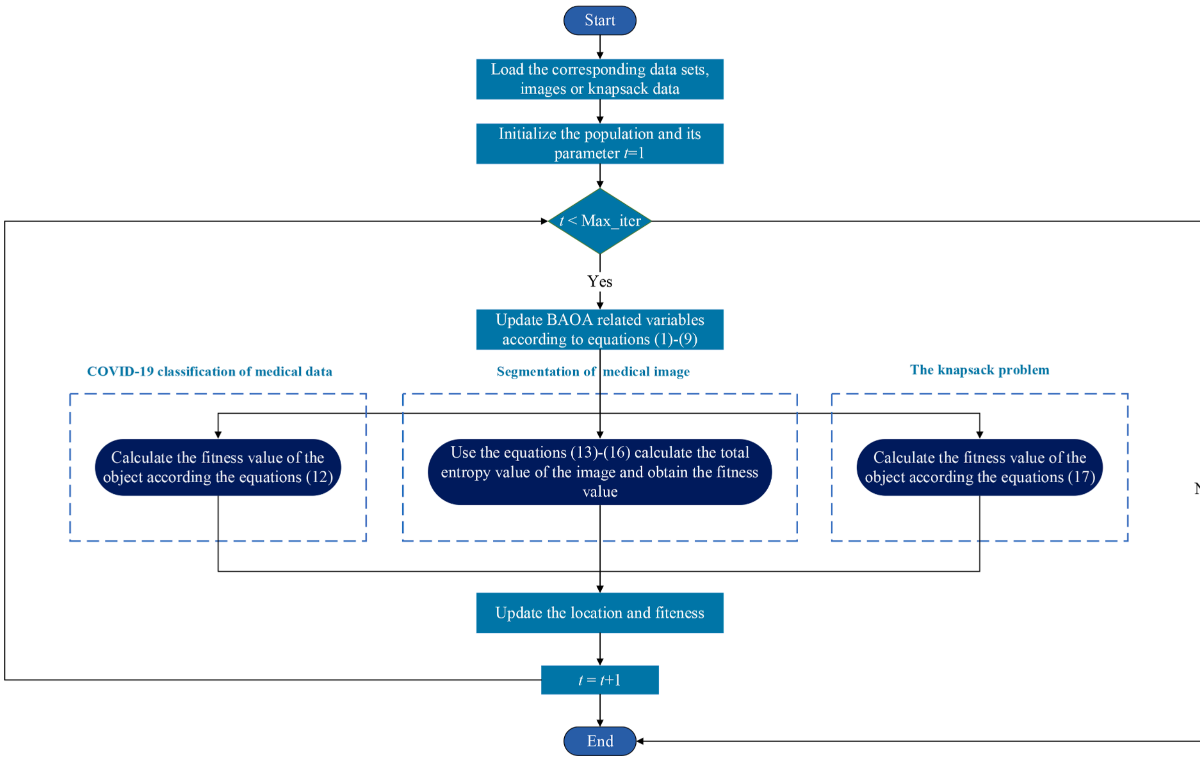


Fig. 5. Flow chart of solving three problems based on BAOA algorithm.

Step 2: Initialize the position, density, volume, and acceleration of the object.

Step 3: Start the iteration and update the related variables of BAOA according to equations (1)-(9).

Step 4: Select equations (12), (16), and (17) as fitness functions and calculate the corresponding fitness value.

Step 5: Update the fitness value of the object. If the current fitness value is less than the optimum, the current value will be taken as the optimum. Besides, the object corresponding to the current fitness value is updated to the optimal position.

Step 6: Judge the size of the iteration number t. If it is less than the maximum iteration, return to Step 3 and repeat the subsequent operations; otherwise, output the optimal fitness value and its corresponding position.

5. Experimental results and evaluation

5.1. Experimental results of COVID-19 classification

To verify the effectiveness of BAOA applied to COVID-19 data classification, this paper uses two COVID-19 datasets from the Kaggle Challenge database, and the specific information is shown in Table 3. Besides, this paper conducts 20 repeated experiments and calculates their average values to ensure the effectiveness of the experiment. At the same time, the experimental results obtained by Binary Particle Swarm Optimization Algorithm (BPSO) (Teng et al., 2017), Binary Grasshopper Optimization Algorithm (BGOA) (Mafarja et al., 2019), Binary Whale Optimization Algorithm (BWOA) (Hussien et al., 2020) and Binary Grey Wolf Optimization (BGWO) (Emary et al., 2016b) are compared with the results conducted by BAOA, as shown in Fig. 6, Table 4 and Table 5.

As can be seen from Table 4 and Table 5, for the Large-scale COVID-19 symptom dataset, using BAOA algorithm for feature selection, the maximum accuracy and average accuracy of the 20 independent repeated experiments are larger than using BPSO, BGOA, BWOA and BGWO, while the minimum and average used number of feature is smaller than using BPSO, BGOA, BWOA and BGWO, which proves that BAOA can use fewer features to achieve higher accuracy and has better classification effect. For Small-scale COVID-19 symptom dataset, due to the small amount of data, the accuracy of the five algorithms can reach 100% at the highest in 20 independent repeated experiments, and only one feature is used at least. However, by comparing the average accuracy and average number of feature of the 20 experiments, we can see that the stability of using BAOA for classification is better than other algorithms.

Table 3
Basic information of COVID-19 datasets.

Datasets	Number of instances	Number of features	Number of categories
Large-scale COVID-19 symptom dataset	5434	20	2
Small-scale COVID-19 symptom dataset	48	4	2

5.2. Experimental results of segmentation of clinical brain lesion

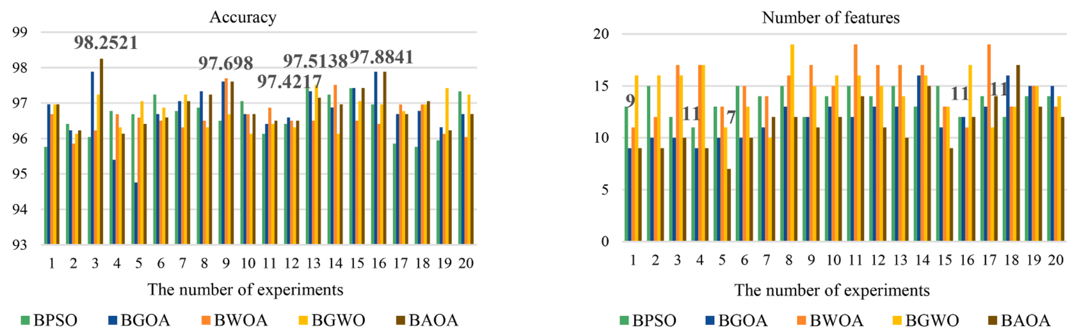
In this paper, representative six images of medical brain images provided by the Second Affiliated Hospital of Dalian Medical University are used. To evaluate the experimental results, three indexes, i.e., Peak Signal to Noise Ratio (*PSNR*), Intersection over Union (*IOU*), and False Positive Rate (*FPR*) are considered.

PSNR can show the distortion degree between segmentation results and the corresponding ground truth:

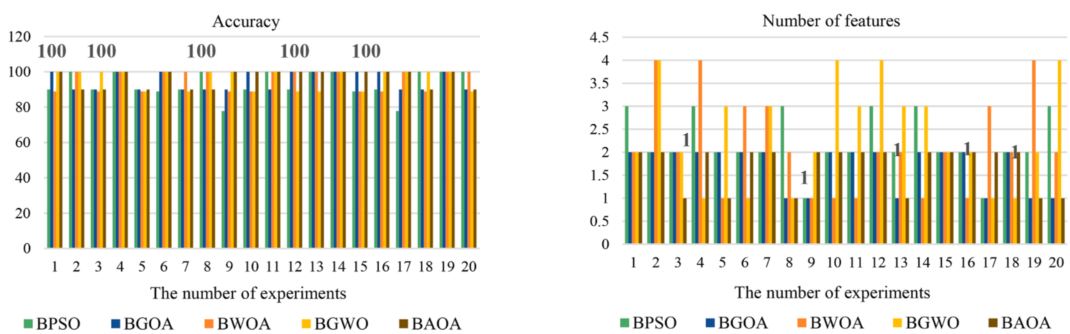
$$MSE = \frac{\sum_{i=1}^{m}\sum_{j=1}^{n}(\mathrm{I}(i,j) - Iout(i,j))^2}{m \times n} \tag{18}$$

$$PSNR = 20 \times \log_{10}\left(\frac{255}{\sqrt{MSE}}\right) \tag{19}$$

where $m \times n$ represents the size of the image, $I(i,j)$ represents the ground



(a) Large-scale COVID-19 symptom dataset



(b) Small-scale COVID-19 symptom dataset

Fig. 6. Experimental results of data classification.

Table 4
Comparison of experimental results based on accuracy.

		BPSO	BGOA	BWOA	BGWO	BAOA
Large-scale COVID-19 symptom dataset	Maximum accuracy	0.974217	0.978841	0.97698	0.975138	**0.982521**
	Average accuracy	0.966298	0.967801	0.966068	0.967864	**0.969135**
Small-scale COVID-19 symptom dataset	Maximum accuracy	**0.1**	**0.1**	**0.1**	**0.1**	**0.1**
	Average accuracy	0.95	0.95	0.9555	0.96111	**0.965**

Table 5
Comparison of experimental results based on number of features.

		BPSO	BGOA	BWOA	BGWO	BAOA
Large-scale COVID-19 symptom dataset	Minimum number of feature	11	9	11	11	**7**
	Average number of feature	13.6	12.15	15.05	14.65	**11.4**
Small-scale COVID-19 symptom dataset	Minimum number of feature	**1**	**1**	**1**	**1**	**1**
	Average number of feature	2.2	**1.7**	2.15	2.4	**1.7**

truth provided by the radiology expert, and $Iout(i,j)$ represents the segmentation result by the proposed algorithm. The smaller *MSE* and the larger *PSNR* are, the better the segmentation results are.

IoU can be used to measure the difference between the segmentation result and the ground truth by calculating the ratio and the union of the intersection:

$$IoU = \frac{TP}{FP + TP + FN} \tag{20}$$

where *TP* is the number of true positive examples, that is, both the segmented image and the ground truth are 1. *FP* represents the number of false positive examples, that is, the pixel value of the segmented image is 1, while the pixel value of the ground truths is 0. *FN* represents the number of false negative examples, that is, the pixel value obtained from the segmented image is 0, while the pixel value of the ground truth is 1. The larger the *IoU* is, the better the segmentation result is.

FPR is used to measure the proportion of the intersection between the segmentation result and the ground truth:

$$FPR = \frac{FP}{FP + TN} \tag{21}$$

where *TN* represents the number of true negatives, that is, both the segmented image and the ground truth are 0. The smaller the *FPR* value is, the better the image segmentation result is.

Brain lesion segmentation results using the proposed BAOA are compared with the experimental results using Binary Artificial Bee Colony algorithm (BABC) (Mustafa Servet Kiran, 2021) and BWOA, as shown in Fig. 7.

Compared with the segmentation results of ABC and WOA in Fig. 7, the proposed BAOA can distinguish the brain lesion and the healthy tissue more clearly. Here, it can see that the location of the segmentation tumor is more accurate and complete, which is helpful for doctors clinically.

By comparing the evaluation indexes of six groups of experiments in

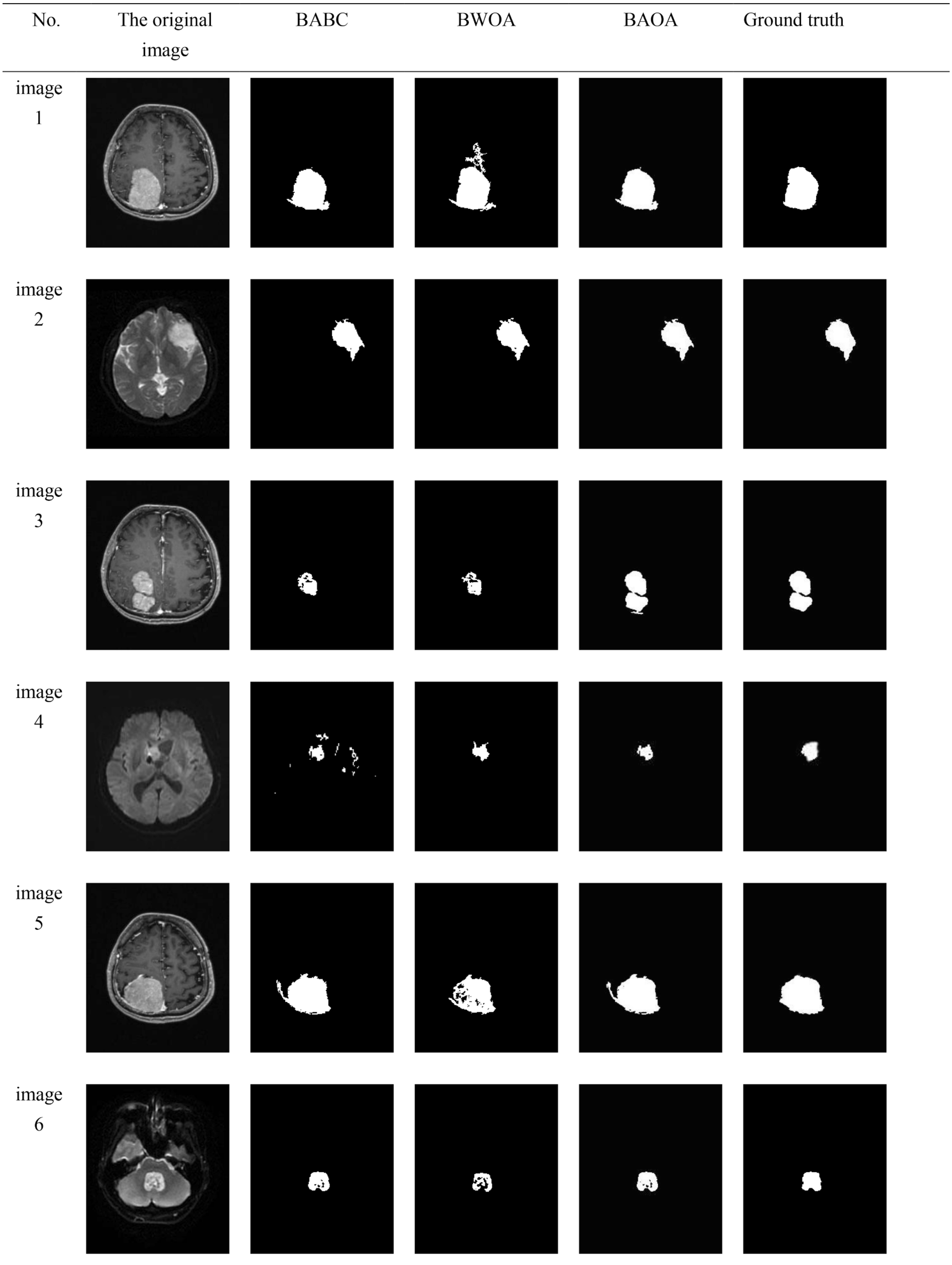


Fig. 7. Comparison of segmentation results and ground truth.

Table 6, it can be seen that for images 1, 2, 5, and 6, the PSNR and IOU by BAOA are larger and MSE and PSR are smaller. For images 3 and 4, the FPR by BAOA in image 3 and the IOU by BAOA in image 4 are larger than that by BWOA. But the other three evaluation indexes by BAOA are better. It can be proved that the brain tumors segmented by the BAOA are closer to the ground truth, which verifies the effectiveness of the proposed method.

Besides, the corresponding statistical analysis of boxplot is provided

Table 6
Evaluation indexes of Fig. 7.

No.	Algorithms	MSE	PSNR	IOU	FRP
image 1	BABC	0.008391	68.892561	0.837307	0.129471
	BWOA	0.014870	66.407702	0.743867	0.226618
	BAOA	**0.003929**	**72.188143**	**0.918266**	**0.065933**
image 2	BABC	0.002716	68.892561	0.892382	0.051995
	BWOA	0.001831	75.503790	0.927449	0.051995
	BAOA	**0.000641**	**80.063110**	**0.973717**	**0.018773**
image 3	BABC	0.016990	65.828773	0.395334	0.005471
	BWOA	0.018442	65.472804	0.341884	**0.002743**
	BAOA	**0.000877**	**78.700323**	**0.969430**	0.005471
image 4	BABC	0.002861	73.566256	0.631068	0.043689
	BWOA	0.002559	74.049303	**0.685185**	0.087963
	BAOA	**0.002409**	**74.312592**	0.675127	**0.000000**
image 5	BABC	0.006022	70.333298	0.893363	0.088864
	BWOA	0.009395	68.401885	0.819587	0.011894
	BAOA	**0.003205**	**73.071878**	**0.940550**	**0.045698**
image 6	BABC	0.001328	76.900410	0.889454	0.040661
	BWOA	0.004028	72.079564	0.654450	0.011780
	BAOA	**0.000626**	**80.167764**	**0.945695**	**0.000000**

as shown in Fig. 8. Compared with BABC and BWOA, the average values of PSNR and IOU by AOA are larger, while the average values of MSE and MRP are smaller. Comparatively speaking, the value of the BAOA is lower, which verifies that the proposed method has less fluctuation and can be more stable.

5.3. *Experimental results of knapsack problem*

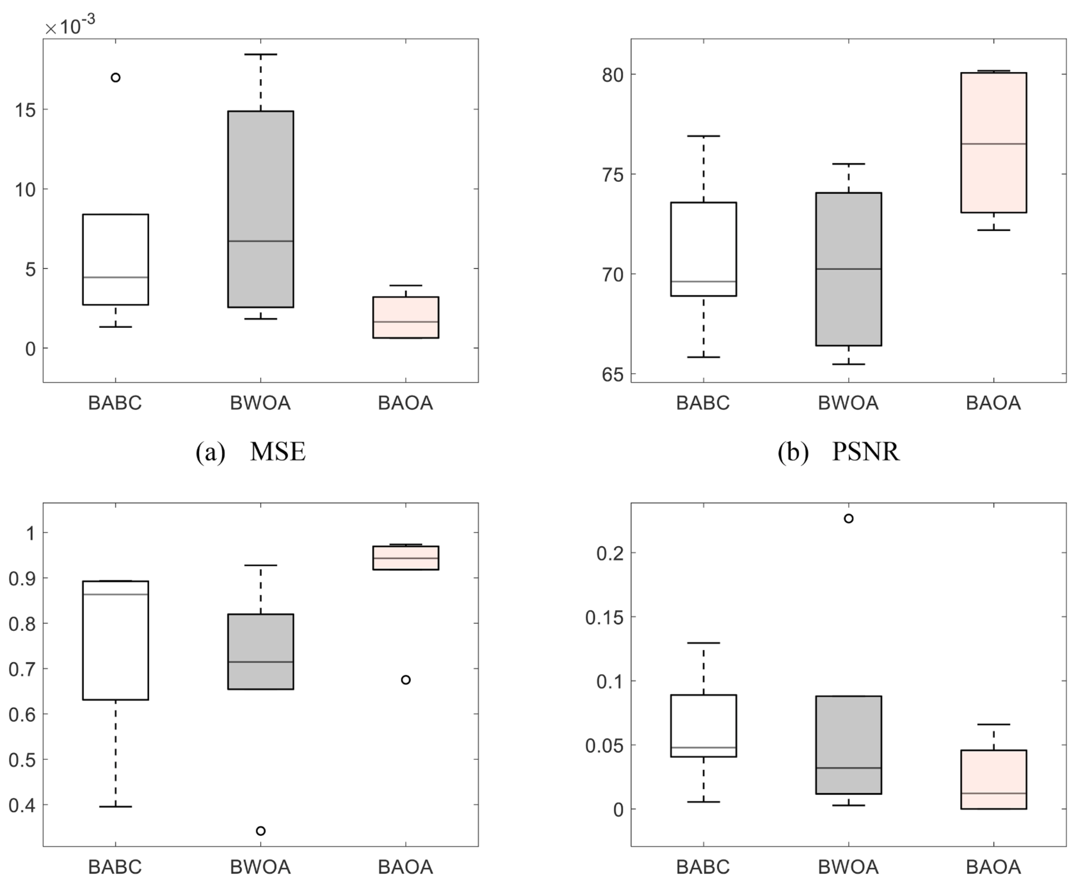
In this paper, the parameters and optimal values of four groups of knapsack problems are given. Through 20 independent repeated tests of the four groups of 0–1 knapsack problems, the optimal experimental value is successfully obtained. The specific experimental information is shown in Table 7. To better observe the experimental process, the minimum of iterations by 20 independent repeated experiments are shown in Fig. 9.

As can be seen from Table 7, BAOA can be used to solve the above four knapsack problems and the optimum can be obtained. As can be seen from Fig. 9, in 20 independent repeated experiments on four groups of knapsacks, the optimum can be obtained in each experiment.

However, for larger knapsacks, more iterations are needed to obtain the optimum in each experiment. Meanwhile, for these four groups of experiments, the minimum number of iterations required to obtain the optimum is 1. it can be seen that the proposed BAOA can effectively solve the knapsack problem.

6. Conclusion and future work

This paper proposes a new BAOA algorithm combined with a novel V-shaped transfer function, which is applied to COVID-19 classification of medical data, segmentation of clinical brain lesion, and the knapsack problem. For COVID-19 data classification, this paper compares the results based on BAOA with those using BPSO, BGOA, BWOA, and BGWO, which shows that the proposed BAOA can obtain a higher classification accuracy with less number of features. In the segmentation of clinical brain lesion, compared with the BABC and BWOA methods, the brain lesion segmented by the proposed BAOA has a clearer contour. For the knapsack problem, four groups of different sizes of cases are carried out and the corresponding optimum can be calculated. According to the above experimental results, BAOA can be well applied in medical data classification, medical image segmentation, and the 0–1



(a) MSE (b) PSNR (c) IOU (d) FRP

Fig. 8. Statistical analysis of Boxplot of Fig. 7.

Table 7
Description of the knapsack problem.

No.	Dimension	Parameter	Optimal value	The optimal value obtained by experiment
1	7	$c = 50$ $w = \{31, 10, 20, 19, 4, 3, 6\}$ $v = \{70, 20, 39, 37, 7, 5, 10\}$	107	107
2	8	$c = 50$ $w = \{31, 10, 20, 19, 4, 3, 6, 3\}$ $v = \{70, 20, 39, 37, 7, 5, 10, 50\}$	150	150
3	9	$c = 300$ $w = \{40, 4, 60, 32, 23, 72, 62, 46, 5\}$ $v = \{5, 10, 47, 5, 4, 50, 61, 87, 60\}$	320	320
4	10	$c = 269$ $w = \{95, 4, 60, 32, 23, 72, 80, 62, 65, 46\}$ $v = \{55, 10, 47, 5, 4, 50, 8, 61, 85, 87\}$	295	295

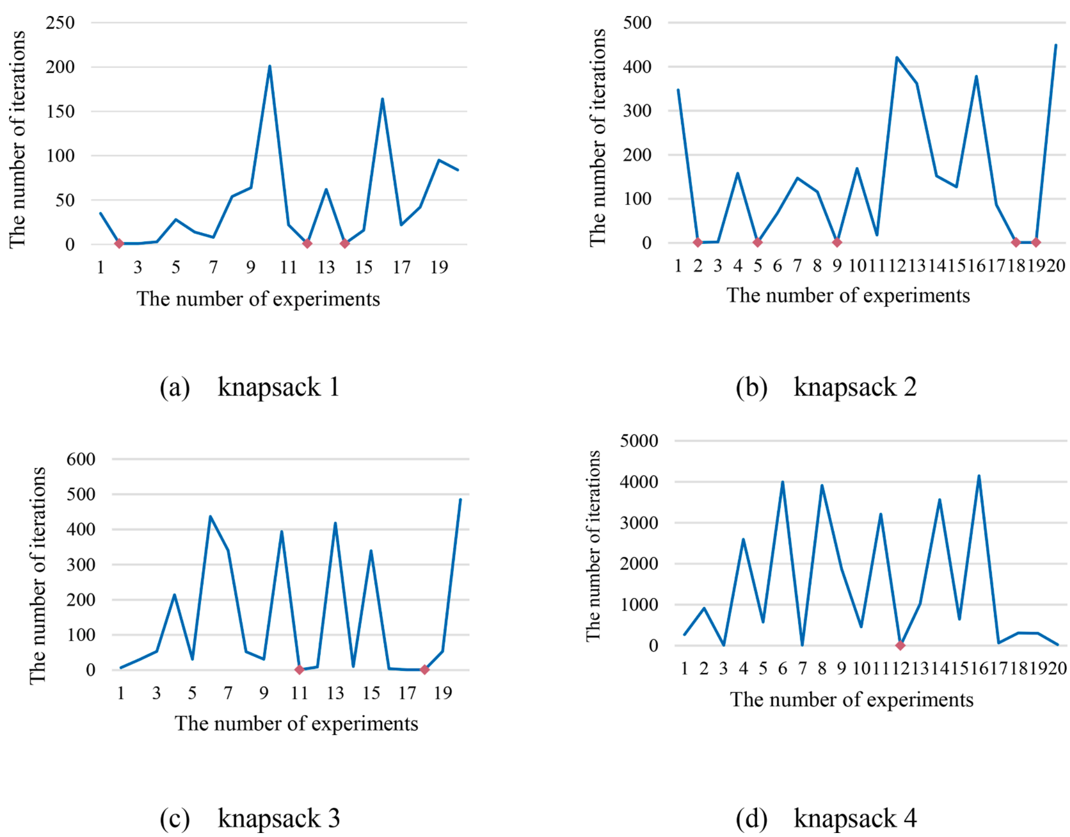


Fig. 9. Comparison of the minimum number for each knapsack.

knapsack problem. Thus, the proposed BAOA algorithm has the ability to tackle the local minimum, which can be efficiently used for multi-variable and multimodal function optimization. Besides, the BAOA has the potential to be applied in clinical diagnosis, management, and business strategies. However, if the amount of experimental data is too large, the processing speed of the proposed method may slow down. In future work, we plan to provide a faster method for real-time applications and further explore applications of BAOA in more areas.

CRediT authorship contribution statement

Lingling Fang: Conceptualization, Methodology, Software, Writing – original draft, Writing – review & editing. **Yutong Yao:** Conceptualization, Methodology, Validation, Writing – original draft. **Xiyue Liang:** Data curation, Investigation.

Declaration of Competing Interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

Data availability

Data will be made available on request.

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