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Improved S-shaped transfer function for binary Whale Optimization Algorithm

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***Abstract*— In traditional binary versions of metaheuristic methods, especially whale optimization algorithm (WOA), the transfer function is used to transform the solution from continuous spaces to binary spaces. In the existing metaheuristic algorithms, the sigmoid transfer function (STF) is assumed to be the same during the learning process, thus the tradeoff between exploration and exploitation is not well balanced. Therefore, designing effective transfer functions to better balance the exploration-exploitation tradeoff is needed to further improve the performance of metaheuristics. In this paper, we propose a improved STF, which can be improved during the learning process, and then apply the proposed framework for WOA, namely improved s-shaped binary WOA (ISBWOA). The experimental results show that is significantly better than the state-of-the-art algorithms for all of the test functions. The very competitive performance compared with the heuristic centralized algorithm shows effectiveness of the proposed algorithms.**

Keywords—Binary Optimization, Sigmoid Transfer Function, Metaheuristic Algorithms, Whale Optimization Algorithm

I. Introduction

Optimization problem is the process of finding the best solution to a problem by the presence of one or more objective functions (maximization or minimization), under the restrictions of a set of constraints.

With the linear or convex objective functions and constraints, the problems are not difficult to solve because there are techniques to obtain the optimal solution. Nevertheless, it may be essential to use other approaches to obtain a near-optimal solution such as metaheuristic algorithms.

In stochastic algorithms, generally, there are two types: heuristic algorithms and metaheuristic algorithms. Metaheuristic is the development version of heuristic, which is beyond or higher level than heuristic algorithms because they are not only simple to find by trial-and-error but also are designed to certain trade-offs of random and local search, and to construct delicate search movement. Heuristics are problem-dependent techniques that used to solve a specific problem while metaheuristics are high-level problem-independent methods that can cover a wide range of problems.

Although metaheuristic algorithms are robust methods to solve optimization problem but most of the original forms of them only support for continuous optimization. Meanwhile, in optimization problems, some models only make sense when variables take on binary values. Therefore, such combinatorial problems require the modifications of continuous form of these algorithms in order to transform to discrete form.

There are two main groups of binarization transforming techniques: two-step binarization and continuous-binary operator transformation [1]. In these two techniques, transfer function (sub-technique of two-step binarization) especially STF is the most frequency applied. This method was used to solve many problems by transforming continuous version to discrete version of many heuristic algorithms. From above case studies, transfer function used a universal and simple mechanism for performing binarizations. Nevertheless, the obtained results are not absolutely appropriate and are concerned to the selection of this method.

That above fascinating challenge motivated us to develop a new methodology for improving the transfer function. Hence, in this paper, we propose a new framework, called Improved S-Shaped Binary Whale Optimization Algorithm (ISBWOA), to transform continuous version of WOA [2] to binary version. The efficiency of this new approach is investigated in order to bypass local minima and convergence speed by balancing exploration and exploitation phase of STF. Furthermore, a comparative study is employed to compare the proposed framework of well-known metaheuristic algorithm WOA to s-shaped binary WOA in order to evaluate its performance.

II. Whale optimization algorithm

A. Whale Optimization Algorithm

WOA is a new bio-inspired metaheuristic algorithm for continuous optimization problems [2]. This algorithm was simulated by the hunting mechanism of humpback whales. To update and improve the position of the whale, this mechanism mainly followed by three rules: encircling prey, bubble-net feeding method, and search for prey.

1) Encircling prey

The mathematical model of this behavior is represented as follows:

$$\vec{D} = \left|\vec{C} \cdot \overrightarrow{X^{*}}(t) - \vec{X}(t)\right|, \tag{1}$$

$$\vec{X}(t+1) = \overrightarrow{X^*}(t) - \vec{A} \cdot \vec{D}, \quad (2)$$

where t is the current iteration, $\overrightarrow{X^*}(t)$ indicates the position vector of the best search agent that has been obtained at time t, $||$ is the absolute value operation, $\cdot$ denotes the element-by-element multiplication, and $\vec{C}$and $\vec{A}$ are two coefficient vectors that are defined as:

$$\vec{A} = 2\vec{a} \cdot \vec{r} - \vec{a}, \quad (3)$$

$$\vec{C} = 2 \cdot \vec{r}, \quad (4)$$

where $\vec{r}$ is uniformly distributed random numbers in $[0,1]$ and $\vec{a}$ decreases linearly from 2 to 0 throughout the iterations (in both exploration and exploitation phases).

2) Bubble-net feeding method

Two approaches *shrinking encircling mechanism* and *spiral updating position* are applied simultaneously to mathematically model the bubble-net behavior of humpback whales.

Shrinking encircling mechanism : In (3), the value range of $\vec{A}$ depends on $\vec{a}$ so that $\vec{A}$ is random value in the range $[-a, a]$ where a is decreased linearly from 2 to 0 throughout the iterations. When we set the random values for $\vec{A}$ in interval$[-1,1]$, the new position will be located between the current position of the agent and the position of the best search agent.

A spiral-based equation that is located between the position of whale and prey to imitate the helix-shaped movement of the humpback whales as follows:

$$\vec{X}(t+1) = \overrightarrow{D'} \cdot e^{bl} \cdot \cos(2\pi l) + \overrightarrow{X^*}(t), \quad (5)$$

$$\overrightarrow{D'} = \left|\overrightarrow{X^*}(t) - \vec{X}(t)\right|, \quad (6)$$

where b is a constant for defining the shape of a logarithmic spiral, l is a random number in $[-1,1]$, and $\overrightarrow{D'}$ indicates the distance of the i-th agent (whale) to the best solution obtained so far (prey).

It is assumed that the probability of 50% to select either the shrinking encircling mechanism or the spiral model to change the location of whales. The mathematical model is illustrated as follows:

$$\vec{X}(t+1) = \begin{cases} \overrightarrow{X^*}(t) - \vec{A} \cdot \vec{D},\ if\ p < 0.5 \\ \overrightarrow{D'} \cdot e^{bl} \cdot \cos(2\pi l) + \overrightarrow{X^*}(t),\ if\ p \geq 0.5 \end{cases}, \quad (7)$$

where p denotes a random number in $[0,1]$.

3) Search for prey (exploration phase)

The approach of search for prey method is similar to shrinking encircling mechanism. However, we do not use $\vec{A}$ with the random values in $[-1,1]$ but $\vec{A}$ is the random values greater than 1 or less than -1. The $\vec{X}_{rand}$ is chosen randomly from the current position. The mathematical model is as follows:

$$\vec{D} = \left|\vec{C} \cdot \vec{X}_{rand} - \vec{X}\right|, \quad (8)$$

$$\vec{X}(t+1) = \vec{X}_{rand} - \vec{A} \cdot \vec{D}. \quad (9)$$

B. Binary Whale Optimization Algorithm

The original form of WOA only supports for continuous optimization. Unfortunately, many problems are in the combinational optimization form, so to deal with this problem, a binary version of metaheuristic, namely s-shaped transfer function was proposed by Mirjalili and Lewis [3]. In this paper, we present the s-shaped version of binary WOA (BWOA), which applied for 3 phases of WOA (encircling prey, bubble-net feeding method, and search for prey).

Firstly, the encircling prey, bubble-net feeding method, and search for prey a transferred to binary version by probability function

$$\sigma = \frac{1}{1+\exp(-\vec{X}(t+1))}, \quad (10)$$

where $\vec{X}(t+1)$ is computed by (2), (5), and (9). The position of whales is updated as follows:

$$\vec{X}(t+1) = \begin{cases} complement(\vec{X}(t)),\ if\ p_B < \sigma \\ \vec{X}(t),\ if\ p_B \geq \sigma \end{cases}, \quad (11)$$

where p_B is a random number in $[0,1]$.

III. IMPROVED SIGMOID TRANSFER FUNCTION FOR WOA

In the STF, the specific sigmoid function is employed to continuous version of WOA to map a real-valued to a probability value in the range [0,1] for moving a binary position. However, in the early steps of algorithm, the STF should provide a high probability to move around search space to give a stronger exploration. On the other hand, in the last stages, the STF should give a low probability of changing all the bit of position in order to provide a higher exploitation. Therefore, STF cannot provide a good balance between exploration and exploitation because this method only use one formula at all iteration of algorithm. To deal with this problem, we propose a new algorithm base on original STF, which can change the value by iterations to balance exploration and exploitation phases. Our proposed improved sigmoid transfer function for WOA (ISBWOA) is formulated as follows:

$$\sigma_{ISBWOA} = \frac{1}{1+\exp(-\alpha \cdot \vec{X}(t+1))}, \quad (12)$$

where α is a control parameter that can be modelled as

$$\alpha = \alpha_{min} + Iter_t * \frac{\alpha_{max} - \alpha_{min}}{Iter_{max}}, \quad (13)$$

where α_{min} and α_{max} are the bounds of control parameter α, $Iter_t$ is the current iteration, and $Iter_{max}$ is the final iteration.

IV. EXPERIMENTAL RESULTS AND DISCUSSION

In this section, we perform the proposed transfer function to compare with original STF for WOA on a unimodal benchmark function and a multimodal benchmark function. Tab. 1 shows the aforementioned functions, where *Dim* is the dimension of the function, *Range* is the range of variation of optimization

TABLE I. DESCRIPTION OF BENCHMARK FUNCTIONS

Type of function	Function	Dim	Range	$f_{\min}$
Unimodal	$F_1(x) = \sum_1^n x_i^2$	30	[-100,100]	0
Multimodal	$F_2(x) = \sum_1^n [x_i^2 - 10\cos(2\pi x_i) + 10]$	30	[-5.12,5.12]	0

TABLE II. PARAMETER SETTING FOR ALGORITHM

Parameter	Value	Parameter	Value
Iteration	500	α_{min}	0.05
Tolerance	10^{-6}	α_{max}	50

variables, and f_{min} is the optimal value of function. The setting for parameters is illustrated in Tab. 2.

Fig. 1 and Fig. 2 show the convergence curves of ISBWOA and BWOA dealing with a unimodal function and a multimodal function. As can be seen from these figures, the ISBWOA outperform in these two benchmark functions comparing to BWOA.

V. CONCLUSION

In this paper, a new improved sigmoid transfer function-based BWOA is proposed and evaluated. In order to assess the performance of ISBWOA, a unimodal benchmark function and a multimodal benchmark function were employed and compared with original sigmoid BWOA. The results show that the new proposed algorithm can improve significantly the performance of STF to avoid local minima and convergence rate.

For future studies, it would be interesting to develop a new transfer function, not only s-shaped but also different type of transfer function such as v-shaped transfer function.

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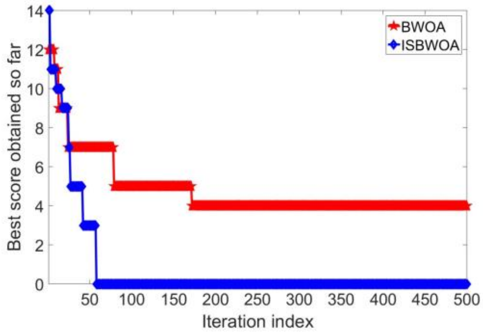

Fig. 1. Comparision between ISBWOA with BWOA on functions $F_1(x)$

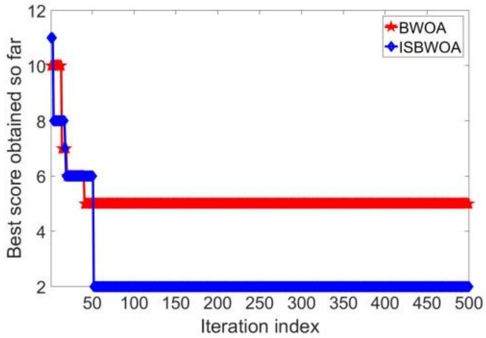

Fig. 2. Comparision between ISBWOA with BWOA on functions $F_2(x)$

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