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Paper:

A Heuristic Algorithm Based on Leadership Strategy: Leader of Dolphin Herd Algorithm (LDHA)

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A heuristic algorithm named the leader of dolphin herd algorithm (LDHA) is proposed in this paper to solve an optimization problem whose dimensionality is not high, with dolphins that imitate predatory behavior. LDHA is based on a leadership strategy. Using the leadership strategy as reference, we have designed the proposed algorithm by simulating the preying actions of dolphin herds. Several intelligent behaviors, such as "producing leaders," "group gathering," "information sharing," and "rounding up prey," are abstracted by LDHA. The proposed algorithm is tested on 15 typical complex function optimization problems. The testing results reveal that compared with the particle swarm optimization and the genetic algorithms, LDHA has relatively high optimization accuracy and capability for complex functions. Further, it is almost unaffected by the inimicality, multimodality, or dimensions of functions in the function optimization section, which implies better convergence. In addition, ultra-high-dimensional function optimization capabilities of this algorithm were tested using the IEEE CEC 2013 global optimization benchmark. Unfortunately, the proposed optimization algorithm has a limitation in that it is not suitable for ultra-high-dimensional functions.

Keywords: leader of dolphin herd algorithm, heuristic algorithm, trial function convergence

1. Introduction

Inspired by the various creatures in nature, humans have designed series of heuristic algorithms by constantly summarizing the survival rules and daily routines of animals and plants. For example, particle swarm optimization (PSO) algorithm [1], ant colony algorithm [2], fish swarm algorithm [3], bacterial foraging algorithm [4], leapfrog algorithm [5], bee colony algorithm [6], bats algorithm [7], monkeys algorithm [8], and wolves algorithm [9]. These algorithms are designed by simulating the predatory behaviors of birds, ants, fishes, Escherichia coli, frogs, bees, bats, monkeys, and wolves, respectively.

Based on niche ideas, Back proposed dolphin partner optimization [10]. However, neither did he fully exploit the concept of dolphin echolocation and the decision making process of the leader, nor did he discuss the convergence of the algorithm. In view of the insufficiency of his theory, this paper designs a heuristic algorithm, which is named leader of dolphin herd algorithm (LDHA) and is based on a leadership strategy. The algorithm is designed by using the echolocation of bats algorithm and abstract dolphins as well as the behaviors of information sharing, producing leaders, rounding up food, and food distribution as reference. We prove LDHA's good convergence and verify its high optimization capability and efficiency by testing this algorithm on 15 typical complex function optimization problems.

2. Leader of Dolphin Herd Algorithm (LDHA)

The preying ability of dolphins is not only stunning but also highly technological. Their superior wisdom enables them to be the leader among all mammals, except human beings. They communicate and prey through echolocation, which is similar to the manner in which bats prey. According to the investigation record, dolphins echolocate using ultrasound waves that have a frequency of more than 200–350 kHz. The hearing range for a human is between 16–20 kHz, and therefore, humans cannot hear the ultrasound waves emitted by dolphins for echolocation. Dolphins can determine the target distance, location, shape, using echolocation. Echolocation is a complex and highly evolved process in which dolphins establish their surrounding sound-image through an analysis of the echoes of the ultrasound waves generated by them. By analyzing the echoes, the dolphins can estimate the distance to nearby obstacles as well as find fishes and other food for them to prey on. From the echoes, dolphins can identify the sizes, shapes, and the direction of the movement of the fishes, making the predation very accurate.

2.1. Some Definitions About LDHA

Sounds enable dolphins to find their paths, acquire food, and communicate with each other. They prey through cooperation. Some basic principles in the process of dolphin preying are as follows.

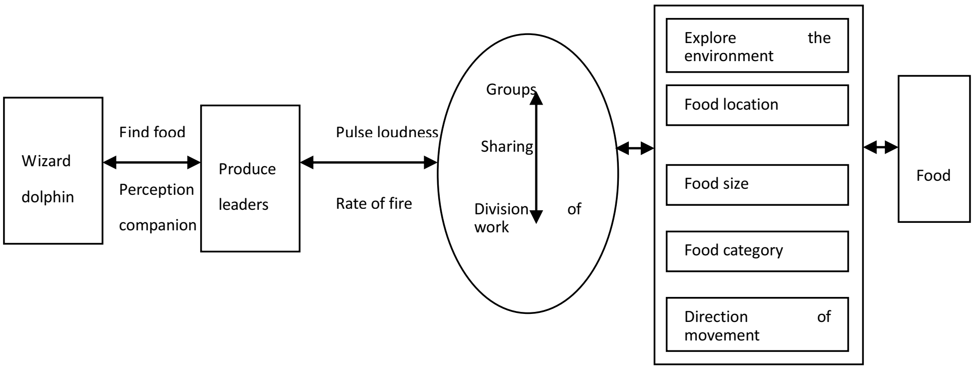

Fig. 1. Dolphin prey model.

Determining Leaders: In order to determine the optimal position in the determining predatory space, dolphins build a three-dimensional scene around them through echolocation, the time delay between producing echoes and detecting echoes, and the binaural time difference as well as the change in the loudness of echoes. The dolphin in the global optimal position is the leader of the entire group and manages some challenging tasks, responsible for group gathering, division of labor, and providing global information for information exchange among group members.

Group Gathering: After the group leader conveys certain related information about the location of food, the entire group gathers at the center where the leader lies. Thus, a predator group gradually comes into being. In this virtual dynamic team, each one does the same thing to become the leader. Therefore, anyone in the optimal position can be a leader in each preying event.

Information Sharing and Rounding up Food: In the process of group gathering, the members exchange information with each other, encircle the prey, and gain the maximum benefit of preying through echolocation. Simultaneously, the dolphin receiving information transfers it to its partners. This communication can be repeated and extended continuously, making the entire group share the information. After information sharing, all the members collaborate, optimize the division of labor, and then prey through depending on the changes in the pulse loudness and emission rate.

Optimizing the Division of Labor: According to the information acquired from all directions, whether a dolphin can be a team leader or an ordinary member depends on the comparison of itself with other team members . In general, the one with the optimal location, the nearest distance, and the best bodily functions becomes the leader of the entire group.

2.2. The Basic Idea of LDHA

LDHA adopts a bottom-up design method focusing on artificial dolphins and a collaborative search path structure based on the division of responsibilities. As shown in **Fig. 1**, the entire preying process of dolphin herds is finally realized through each dolphin's probing into the features of food and environmental information, artificial dolphins' mutual information sharing and interactions, as well as individual behavioral decision making concerning its duties.

When the acoustic detection beam emitted by a dolphin encounters fishes or other targets, echoes are produced. Once they return to the dolphin, these echoes are received by the dolphin's sense organs. Through an analysis of the loudness of echoes, the change in frequency, and the time interval between the produced echoes and the received echoes, dolphins can estimate the distance to the probe target, the size of the fish, and the run away velocity. They adjust their direction and speed from time to time. The nearer they are to the food, the quicker is the emission of the acoustic detection beams, reaching hundreds of times per second. As a result, dolphins can prey with a high accuracy.

LDHA iterates the information received through the echolocation to determine the optimal position in the dolphin herds constantly, which is also the solution of the optimization problem sought in this study. To solve this problem, dolphins take five steps, namely initializing dolphins, optimizing the division of labor, information sharing, group following, and rounding up food and food distribution.

2.3. Decomposition Process

2.3.1. Initializing Dolphins

The purpose of this phase is to distribute each member in the group evenly in the domain of the objective function. N and D denote the scope of the dolphins and the dimension of the search space, respectively. Then, the location of artificial dolphin i can be derived as

$$X_i = (x_{i1}, \dots, x_{id}, \dots x_{iD})$$
$$x_{id} = x_{\min} + \text{rand} \times (x_{\max} - x_{\min}) \quad \dots\dots \quad (1)$$

In this formula, rand is a random number distributed evenly in the interval $[0, 1]$, while $x_{\max}$ and $x_{\min}$ are the corresponding upper and lower limits of the search space.

2.3.2. Optimizing the Division of Labor

Anyone can act as the "guide" in the dolphins' predatory space. In the beginning, the entire group is distributed randomly at any position of the space. If one of them finds food, the "guide" will transfer the food information to others correspondingly through the strategy of echolocation.

After the dolphins acquire information, they will find their own team members to form virtual teams. In order to achieve the most accurate optimization result, define each dolphin $X_i\,(i=1,2,\ldots,n)$ as the center and calculate the distance X_{ij} between dolphin $X_j\,(j=1,2,\ldots,n)$ and dolphin X_i (this distance can be calculated according to the location formula of two dolphins). Next, rank the distances of two dolphins in an ascending order. Then, according to the result, select the nearest m dolphins for each individual to form its virtual team. The distance between the two dolphins is calculated as follows:

$$X_{ij}=\sqrt{\overrightarrow{X_i-X_j}\cdot\overrightarrow{X_i-X_j}},\quad (i,j\in 1,2,\ldots,n) \quad . \quad (2)$$

More than one virtual team exists in the entire dolphin herd, and each team has its own local leader. Compared with each other, the team leader is decided among the leaders of the members. According to LDHA, the leader of each virtual team is determined by the local optimal value of the fitness function, whereas the leader of the entire herd is generated from each virtual team by constant iteration. When the value reaches the maximum number of iterations in the process of food gathering, the leader of the entire herd is decided (namely, the global optimal value of the fitness function).

2.3.3. Information Sharing

After the leader is decided, the leader can exchange information with its group members to determine their best locations and fitness values. This type of communication can be realized several times, and the dolphins with excellent characteristics can be accepted easily by other members. Therefore, information sharing enables dolphins to approach food, form encirclement gradually, and then, prey in an ordered manner under the leader's top-down guidance.

2.3.4. Group Following and Rounding Up Food

When the leader receives food information from the "guide" it notifies other members to surround and assemble at it's location through echolocation. For ordinary members, an effective location update is the critical step in the entire process of preying.

As for location update, if the value of r_m, a random number generated in the interval [0, 1] is smaller than that of θ (a predetermined threshold), the i-th dolphin does not need to update its location. Otherwise, it has to update its location and round up food centering on the leader. Here, we use the pulse loudness $A(i)$ and emission rate $R(i)$ to update the process of iteration. In general, while approaching food, the pulse loudness decreases and emission rate increases gradually. If $A(i)=0$, the i-th dolphin finds a prey and will stop making any sound temporarily. Eqs. (3) and (4) are update equations of the pulse loudness and emission rate, respectively.

$$A^{t+1}(i)=\alpha A^t \quad \ldots\ldots\ldots\ldots \quad (3)$$

$$R^{t+1}(i)=R^0(i)\times[1-\exp(-\gamma t)] \quad \ldots\ldots \quad (4)$$

In the above formulas, a and y are constants ($1<\alpha<1$, $\gamma>0$). It is not difficult to find that as $t\to\infty, A^t(i)=0, R^t(i)=R^0(i)$, the updated location X_i^{t+1} can be calculated as

$$X_i^{t+1}=\begin{cases} X_i^t & r_m<\theta \\ X_i^t+\varepsilon A^t(i) & r_m<\theta \end{cases} \quad \ldots\ldots \quad (5)$$

where, ε denotes a D-dimensional random vector belonging to the interval $[0,1]$ and $A^t(i)$ denotes the pulse loudness at time t.

For ordinary members, they may not locate food. Therefore, after rounding up food, the coordinates of dolphins are updated as follows

$$x_{id}^{t+1}=\begin{cases} x_{\max} & x_{id}^{t+1}>x_{\max} \\ x_{\min} & x_{id}^{t+1}<x_{\min} \end{cases} \quad \ldots\ldots\ldots \quad (6)$$

Having determined leader's position,the leader in the dolphin herd exchanges information with its members to inform them about its location and fitness value, so that all the members can adjust their own locations according to the leader's fitness value. This is the only manner in which the herd can form the encirclement in an orderly manner, make the overall situation optimal, and get the maximum benefit of preying.

2.3.5. Food Distribution and States Recovery

After forming the encirclement, the dolphins update their locations, narrow down the scope, and then prey collaboratively. The food is not distributed as per their credits. Instead, the dolphin, in the optimal position of the encirclement both globally and locally, stops to wait for subsequent dolphins' gathering, and then, prey together. After completing the entire process, dolphins recover to their random states in the predatory space to prepare for the next prey.

3. Calculation Steps of LDHA

Based on the above methods and algorithms of dolphin preying, the calculation steps of LDHA are designed as follows:

Step 1: Initialize the dolphin herd. Initialize its total number n and the maximum number of iterations $\max h$. According to Eq. (1), the locations of dolphins can be initialized.

Step 2: Optimize the division of labor. Form each dolphin's virtual team according to the distance formula, determine the optimal location of the team by comparing the fitness value of each team, and then elect the leader of each virtual team. Finally, generate the global optimal value by comparing

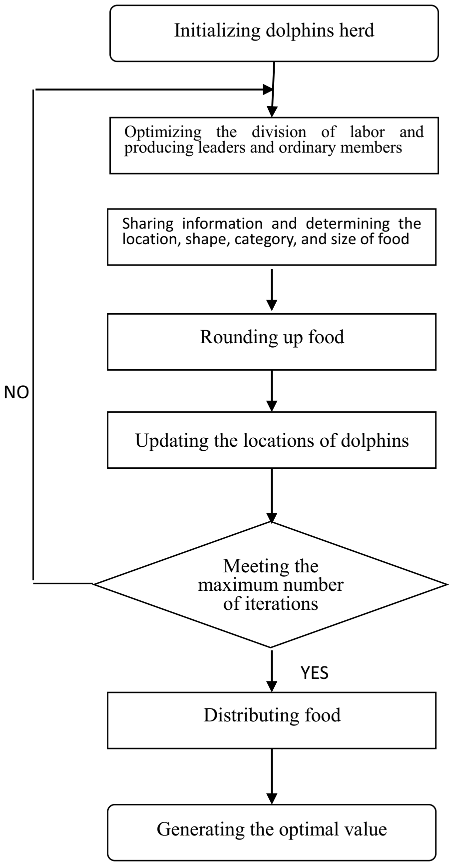

Fig. 2. Algorithm flowchart of LDHA.

the fitness value of each team and produce the leader of the entire herd.

Step 3: Exchange information. Having determined its location, the leader communicates with its members through echolocation to acquire some information about location and fitness value. Exchanging information helps them to update locations in the next step.

Step 4: Round up food. Eq. (6) is used to deal with cross-border situations among ordinary members, and Eq. (5) is applied to iterate the locations of group members, form encirclement, and update locations.

Step 5: Perform iterations in a circular manner until it reaches the maximum number of iterations. Once the condition is satisfied, exit the loop, and record the result. Otherwise, skip to Step 2.

Specific algorithm flowchart of LDHA is shown in **Fig. 2**.

The optimization process diagram of the algorithm simulating dolphin preying is shown in **Fig. 3**.

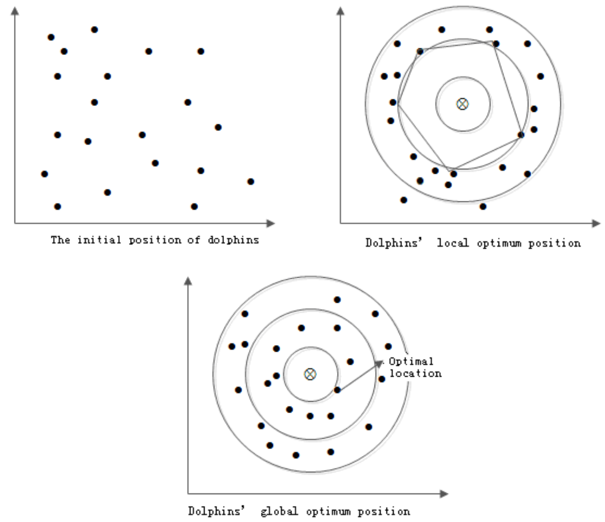

Fig. 3. Optimization process diagram of the algorithm analoging dolphin prey.

4. Analysis of the Convergence of LDHA

Theorem 1: The sequence solutions in LDHA are finite homogeneous Markov chains.

Proof: LDHA initializes the location of the dolphin herd randomly and repeats location iteration and prey constantly. Because each step in the process of optimization has no aftereffect, the race sequence of LDHA is a Markov chain. Let $H_k = \{X_1, X_2, \ldots, X_N\}$ denote the dolphin group in the k-th iteration step, in which N denotes the total number of dolphins and X_i denotes the location of the i-th dolphin.

The finiteness of dolphin herd H_k makes itself a finite homogeneous Markov chain. Because dolphins behave independently and randomly in collaborative moving and rounding up prey, and each time the updated dolphin locations inherits the winning choice, the emergency of the $(k+1)$-th generation of dolphin herds (H_{k+1}) can only depend on the k-th generation (H_k). It is not related to the transition probabilities of the dolphin herd and algebra k. Therefore, the sequence of optimal solutions of H_k through constant updates is a finite homogeneous Markov chain.

Theorem 2: The finite homogeneous Markov chains composed of the sequence solutions of LDHA are ergodic chains.

Proof: Suppose that the state transition matrix of Markov chain in LDHA is $P_{ij} = P\{H_{k+1} = j | H_k = i, k \geq 1\}$. As the probability only relates to the state of i, j, and $H_k > 0$, P is a positive definite matrix. According to Definition 1 in [9], the sequence solutions in LDHA are irreducible Markov chains. Besides, they are aperiodic chains taking Definition 2 in [9] and $P_{ij} \geq 0$ into consideration. Define D as the search space of the dolphin herd and make $\varepsilon = \max\{P_{ij} : \forall i, j \in D\}$. As $0 < P_{ij} < 1$, $u_i = \sum_{k=1}^{\infty} k P_{ij}^k \leq \sum_{k=1}^{\infty} k \varepsilon^k < \infty$ can be deduced according to the Canchy–Riemann equation and Lemma 2 in [9].

Table 1. Unimodal functions.

Function	Expression	Dimension	Ranges	Theoretical optimal solution
Easom	$f(X) = -\cos(x_1)\cos(x_2) \times \exp\left(-(x_1-\pi)^2-(x_2-\pi)^2\right)$	2	$[-100, 100]$	$\min f = -1$
Matyas	$f(X) = 0.26\left(x_1^2+x_2^2\right) - 0.48x_1x_2$	2	$[10, 10]$	$\min f = 0$
Trid6	$f(X) = \sum_{i=1}^{D}(x_i-1)^2 - \sum_{i=2}^{D} x_i x_{i-1}$	6	$[-36, 36]$	$\min f = -50$
Sumsquares	$f(X) = \sum_{i=1}^{D} i x_i^2$	10	$[-10, 10]$	$\min f = 0$
Sphere	$f(X) = \sum_{i=1}^{D} x_i^2$	30	$[-1.5, 1.5]$	$\min f = 0$

Table 2. Multimodal functions.

Function	Expression	Dim	Ranges	Theoretical optimal solution
Booth	$f(X) = (x_1+2x_2-7)^2 + (2x_1+x_2-5)^2$	2	$[-10, 10]$	$\min f = 0$
Bohachevsky1	$f(X) = x_1^2+2x_2^2-0.3\cos(3\pi x_1)-0.4\cos(4\pi x_2)+0.7$	2	$[-100, 100]$	$\min f = 0$
Eggcrate	$f(X) = x_1^2+x_2^2+25(\sin^2 x_1+\sin^2 x_2)$	2	$[-\pi, \pi]$	$\min f = 5.5281 \times 10^{-53}$
Schaffer	$f(X) = 0.5 + \frac{\left(\sin\sqrt{x_1^2+x_2^2}\right)^2-0.5}{\left(1+0.001(x_1^2+x_1^2)\right)^2}$	2	$[-100, 100]$	$\min f = 0$
Six Hump Camel Back	$f(X) = 4x_1^2-2.1x_1^4+1/3x_1^6+x_1x_2-4x_2^2+4x_2^4$	2	$[-5, 5]$	$\min f = -1.0316$
Bohachevsky3	$f(X) = x_1^2+2x_2^2-0.3\cos(3\pi x_1+4\pi x_2)+0.3$	2	$[-100, 100]$	$\min f = 0$
Bridge	$f(X) = \frac{\sin\sqrt{x_1^2+x_2^2}}{\sqrt{x_1^2+x_2^2}} + \exp\left(\frac{\cos 2\pi x_1+\cos 2\pi x_2}{2}\right) - 0.7129$	2	$[-1.5, 1.5]$	$\max f = 2.0174$
Rastrigin	$f(X) = \sum_{i=1}^{D}[x_i^2-10\cos(2\pi x_i)+10]$	60	$[-10, 10]$	$\min f = 0$
Quadric	$f(X) = \sum_{i=1}^{D}\left(\sum_{k=1}^{1} x_k\right)^2$	120	$[-30, 30]$	$\min f = 0$
Ackley	$f(X) = -20\exp\left(-0.2\sqrt{\frac{1}{D}\sum_{i=1}^{D} x_i^2}\right) - \exp\left(\frac{1}{D}\sum_{i=1}^{D}\cos 2\pi x_i\right) + 20 + e$	200	$[-32, 32]$	$\min f = 8.8818 \times 10^{-16}$

Therefore, the finite homogeneous Markov chains composed of the sequence solutions of LDHA are ergodic chains. According to Theorem 2, the Markov chains composed of the sequence solutions of LDHA are ergodic chains and satisfy the condition in [11] that the evolutionary algorithm converges to the optimal solution with the probability of 1. Therefore, according to Theorem 4 in [9], the optimal solution in LDHA is converged with the probability of 1.

5. Experiments and Analysis

In order to fully test the performance optimization of LDHA, in this study, we conduct experiments using the standard test functions in [12–14]. The results are shown in **Tables 1** and **2**. The five standard complex functions in **Table 1** are unimodal functions, and the 10 standard complex functions in **Table 2** are multimodal functions. **Figs. 4–6** shows the characteristics of the local optimum and global optimum of test functions in various types (fitness functions). The experiments are conducted by us-

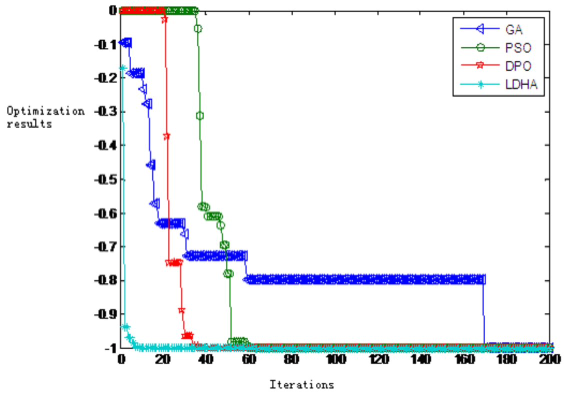

Fig. 4. Representation of function Easom.

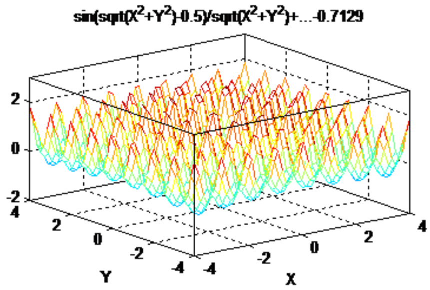

Fig. 5. Representation of function Bridge.

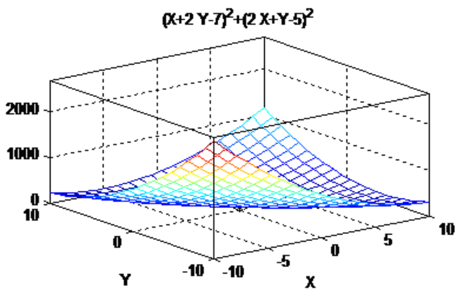

Fig. 6. Representation of function Booth.

ing a PC equipped with the simulation program written in MATLAB2012b, Windows 7 operating system, AMD Athlon 640 quad-core processor, and 3 GB RAM.

5.1. Analysis of Standard Test Functions

A simple analysis of the above mentioned standard functions is as follows:

The only extreme in the definition domain of a unimodal function is the global optimum, such as function Easom and function Ackley. **Fig. 4** shows the figure of function Easom. There exist multiple extremes in the definition domain of multimodal functions, and its general algorithm can easily generate the local optimum or fluctuate among local extremes. Multimodal functions are often used to test the global search capacity of the algorithm.

Functions can be classified as separable and non-separable functions. If a function has N variables and can be expressed by the sum of N single variable functions, it is a separable function. Otherwise, it is non-separable. **Fig. 6** illustrates function Booth, which is a multimodal separable function. In **Fig. 5**, function Bridge is multimodal and non-separable. Due to the complexity among the variables in non-separable functions, it is relatively more difficult to realize function optimization than in the case of separable functions.

Besides, the indicator of the dimension function is of great importance to test intelligent optimization algorithms. Some functions have a very good low-dimensional effect; however, they have poor high-dimensional effect. Therefore, the test functions in **Table 1** can be used to test the performance of LDHA fully and comprehensively.

5.2. Comparative Analysis of Algorithms

In order to compare the performance of LDHA, which is based on leadership strategy, we test other heuristics, including genetic algorithm (GA) [18–20] and PSO [21–23]. In this study, we adopt the standard GA algorithm without any elitist strategy, and the probabilities of mutation and crossover in GA are 0.05 and 0.95, respectively. Further, we use the standard version of PSO whose learning parameter α is 2 and inertia is 1. Approximately 1000 function values are involved in each implementation, and the running time is less than 5 s. Moreover, having attempted a number of population quantities ranging from $n = 2$ to $n = 200$, we proved that the value of n generated from 10 to 50 is sufficient for most questions. Therefore, a fixed value of $n = 40$ is applied to all simulations. **Table 2** shows the values of test functions in the form of "mean $\pm$ standard deviation" (seeking the success rate of global optimum).

As can be seen from **Table 3**, PSO is superior to GA, and GA is superior to any other algorithms in terms of the accuracy and efficiency of calculation. However, LDHA improves the rate optimization and accuracy of calculation by citing echolocation and iterating through the pulse loudness and emission rate.

In order to visualize the comparison among LDHA, GA, and PSO, **Figs. 7–11** show the convergence curves of iterations and values of objective functions by testing five different standard functions with the same nature.

It is apparent from **Figs. 7–11** that LDHA outperforms other algorithms in terms of the calculation accuracy and the convergence rate.

If the frequency change is replaced by the entity set $A(i) = 0$ and $R(i) = 1$ of a random parameter, LDHA is transformed into PSO. Similarly, if the pulse loudness and emission rate are fixed, say $A(i) = R(i) = 0.65$, LDHA is almost degraded to a simple harmony search (HS). This is attributed to the fact that the change in wavelength or frequency acts as a change in pitch in essence, and the radiation pulse in LDHA is similar to the harmonic acceptance rate in HS (here, somewhat distorted). LDHA compares the maximum values directly and generates the optimal value by comparing the local optimal values through the

Table 3. Comparison between LDHA and GA, POS, and DPO.

Function	GA	PSO	DPO	LDHA
Easom	19239± 3307 (92%)	17273± 2929 (90%)	3528± 265 (99%)	4519± 405 (99%)
Matyas	52124± 3277 (98%)	69224± 573 (98%)	4923± 448 (98%)	7923± 645 (98%)
Trid6	55723± 8901 (90%)	32756± 5325 (98%)	34657± 3675 (99%)	33756± 5345 (100%)
Sumsquares	25412± 1237 (100%)	17040± 1123 (100%)	2156± 317 (100%)	1152± 245 (100%)
Sphere	227329± 7572 (95%)	14522± 1275 (97%)	15378± 6780 (99%)	5715± 678 (100%)
Booth	89325± 7914 (95%)	43219± 439 (97%)	43579± 537 (100%)	4315± 439 (100%)
Bohachevsky1	33929± 1567 (98%)	53247± 472 (90%)	6573± 457 (100%)	5379± 472 (100%)
Eggcrate	524579± 3369 (97%)	45237± 432 (99%)	9765± 613 (99%)	8928± 732 (100%)
Schaffer	70925± 7652 (90%)	55970± 4223 (92%)	7657± 4312 (99%)	6957± 2317 (100%)
Six Camel Back	54077± 4997 (89%)	23992± 3755 (93%)	6789± 4532 (100%)	14537± 3479 (100%)
Bohachevsky3	45796± 2254 (98%)	34578± 342 (93%)	78935± 4537 (99%)	7543± 2096 (100%)
Bridge	55643± 4456 (99%)	45329± 235 (94%)	4537± 457 (100%)	1068± 756 (100%)
Rastrigin	110523± 5199 (77%)	79491± 3715 (90%)	8967± 6857 (99%)	9792± 5430 (100%)
Quadric	67453± 2199 (89%)	37193± 205 (97%)	25789± 4321 (99%)	11756± 3409 (99%)
Ackley	32720± 3327 (90%)	23407± 4325 (92%)	67534± 5674 (100%)	27860± 4325 (100%)

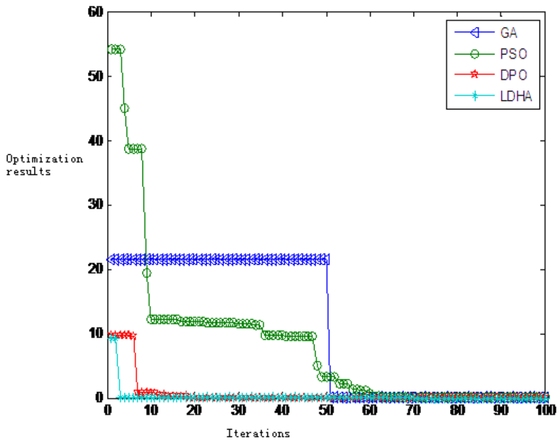

Fig. 7. Convergence curve comparison of function Eggcrate.

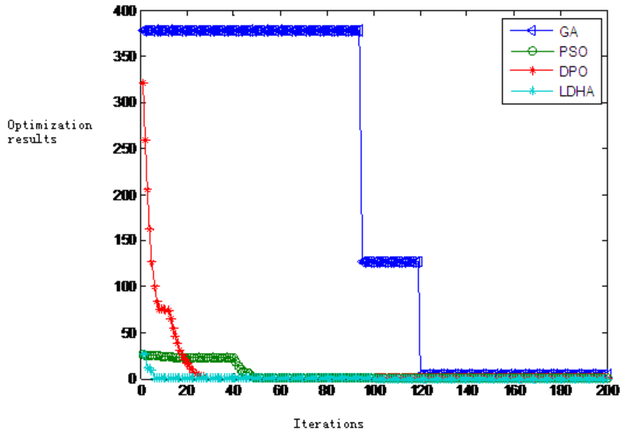

Fig. 9. Convergence curve comparison of function Booth.

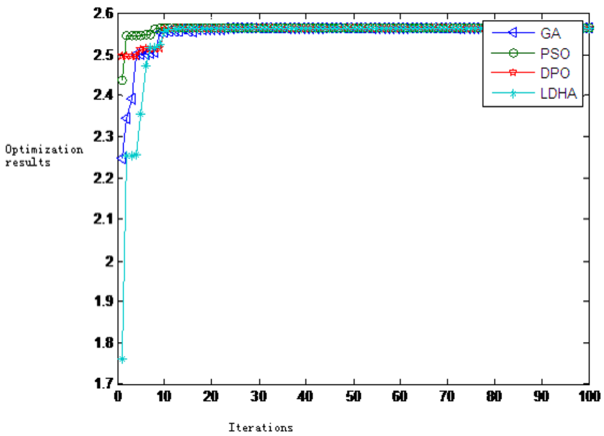

Fig. 8. Convergence curve comparison of function Bridge.

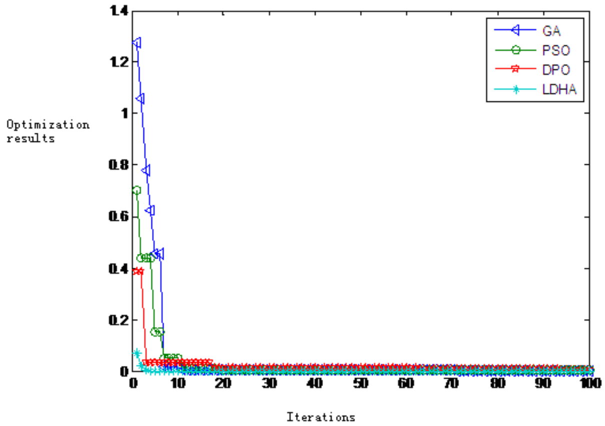

Fig. 10. Convergence curve comparison of function Ackley.

fitness function. Besides, LDHA does not adopt entity set or random parameters, nor does it use fixed loudness or frequency. Instead, LDHA generates these values randomly, which is more practical and significantly improves the optimization accuracy.

5.3. Optimization Test by Ultra-High-Dimensional Function

To validate the algorithm used in the different dimension functions, especially ultra-high-dimensional functions in [23] As shown in the following Eq. (7), this al-

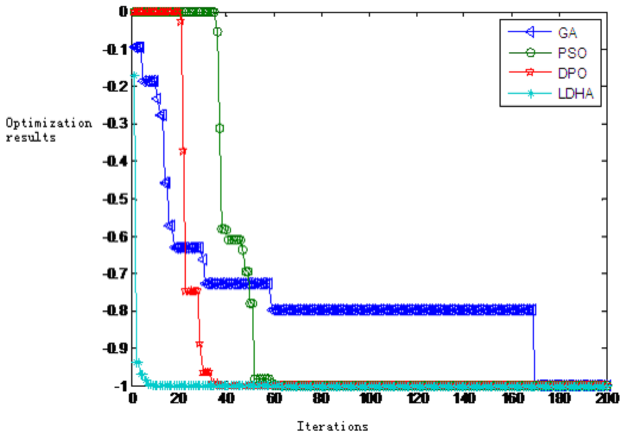

Fig. 11. Convergence curve comparison of function Easom.

gorithm was tested. The results are shown in **Table 4**.

$$\begin{cases} f(Z)=\sum_{i=1}^{|S|}\omega_i\Bigg[-20\exp\left(-0.2\sqrt{\frac{1}{D}\sum_{j=1}^{D}x_{ij}^2}\right) \\ \qquad -\exp\left(\frac{1}{D}\sum_{j=1}^{D}\cos 2\pi x_{ij}\right)+20+e\Bigg] \\ S=\{50,50,25,25,100,100,25,25,50, \\ \qquad 25,100,25,100,50,25,25,25\} \\ D=\sum_{i=1}^{|S|}S_i=1000 \\ y=x-x^{\mathrm{opt}} \\ y_i=y\left(P_{[C_{i-1}+1]}:P_{[C_i]}\right), \quad i\in\{1,\ldots,|S|\} \\ z_i=\Lambda^{10}T_{asy}^{0.2}\left(T_{osz}(R_i y_i)\right), \quad i\in\{1,\ldots,|S|\} \\ R_i: a\,|S_i|\times|S_i| \\ x\in[-32,32]^D, f(x^{opt})=0 \end{cases} \tag{7}$$

As shown in **Table 4**, the calculation precision of LDHA algorithm is higher, operation time can be accepted, in the function of no more than 200 d dimension. Unfortunately, the test time is more than 253 h and the calculation error algorithm is relatively large for ultra-high-dimensional function optimization; this leads to senseless results. Therefore, the algorithm is not suitable for ultra-high-dimensional function optimization (more than 200 d). This is a limitation of the algorithm.

6. Conclusion

According to the behavioral characteristics of dolphin herd preying, a global optimization algorithm based on leadership strategy is proposed in this paper. In order to survive, the whole herd preys under the guidance of artificial dolphins. Through the process of searching for food, transforming roles, and rounding up food, the dolphin herd realizes the aim of global optimization step by step. The result of testing this algorithm on 15 basic functions as well as the comparison of two classic intelligent algorithms proves the good convergence and optimization capability of LDHA. As for complex functions, LDHA is almost unaffected by the unimodality, multimodality, or dimensions of functions. Moreover, this algorithm is concise and efficient as the parameters needed in LDHA are extremely few. The limitation of the algorithm is that it is not suitable for high-dimensional function optimization problems.

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Table 4. The results of the test.

Function	Dimension	Test times	Calculation accuracy	Optimum success rate	The average operation time
Sumsquares	10	50	1152± 245	100.0%	3.5 s
Sphere	30	50	5715± 678	100.0%	15.7 s
Rastrigin	60	100	9792± 5430	100.0%	32.6 s
Quadric	120	100	11756± 3409	99.7%	43.7 s
Ackley	200	200	27860± 3341	96.6%	230.5 s
Equation (7)	1000	20	5673281± 673524	45.7%	253 h

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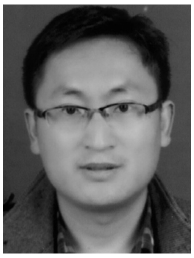

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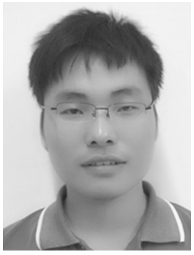

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