2010 Fourth International Conference on Genetic and Evolutionary Computing

Fish Migration Optimization Based on the Fishy Biology

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***Abstract*—In this paper, we propose Fish Migration Optimization (FMO) method based on a verified equation of the fish swim in the fish biology for solving numerical optimization problems. Inspired by the fish migration, the migration and the swim model are integrated into the optimization process. Four benchmark functions are used to test the convergence, the accuracy and the speed of FMO, and the experimental results are compared with PSO. The experimental result indicates that the proposed FMO presents higher accuracy and convergence speed.**

Keywords-optimization; Fish Migration Optimization (FMO); swarm intelligence

I. INTRODUCTION

People have lots of things to learn from Mother Nature. From the evolution theory to different behaviors of creatures to survive, many algorithms for solving optimization problems are proposed and well used in many applications. For example, genetic algorithms (GA) have successfully been used in the internet service [7] and impedance measurements [8]; particle swarm optimization (PSO) techniques have successfully been used to design antennas [15] and to construct parameters in neural network systems [9]; ant colony optimization (ACO) techniques have successfully been used to solve the traveling salesman problem (TSP) [6] and the routing problem of networks [13]; artificial bee colony (ABC) techniques have successfully been used to solve the lot-streaming flow shop scheduling problem [12]; cat swarm optimization (CSO) techniques have successfully been used to discover proper positions for information hiding [14] and to adjust parameters for the SVM [10]. Inspired by the migration behavior and the movement model of fish, we propose fish migration optimization (FMO) in this paper base on utilizing the biological characteristic of fish migration and the swim equation in the fish biology.

The paper is organized as follows: In session 2, the background about swarm intelligence and the fish migration characteristics are given. In session 3, we describe the detail of the proposed fish migration optimization. The experimental results are compared with PSO in session 4. Finally, we give the conclusion in session 5.

II. BACKGROUND OF FISH MIGRATION OPTIMIZATION

In Mother Nature, every species has its way to against the dangerous environment and the natural enemy to survive. Some species move based on purposes, and this behavior is called migration. The scholars of fish biology conclude the causes of fish migration in three objectives: the feeding migration, the breeding migration, and the over-wintering migration [1, 3-5, 11]. The species we choose to construct fish migration optimization is grayling, which is a kind of migrating fish. Fig. 1 shows the grayling's life cycle, where 0+ to 4+ denote different age groups of the grayling in five years, F_2 to F_4 represent the fecundities of the individuals moving back to the birthplace, and S_1 to S_4 are the number of the survival individuals.

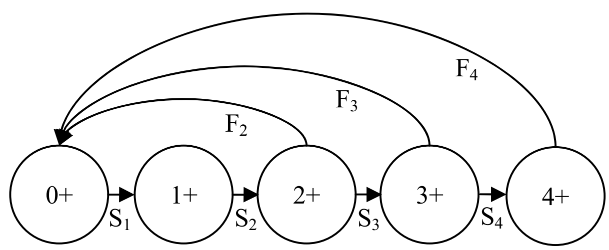

Figure 1. Life cycle graph of the grayling. (adopted from [5])

Assume the life cycle of the grayling is four years, and the life cycle can be divided into five stages. The legends are described as follows [5]:

- Stage 0+: This stage represents the newborn and young fish, whose age is from 0 to 1 year. The grayling in this stage are ready to leave its birthplace and will move on searching for food sources for survival.
- Stage 1+: The juvenile grayling, whose age is from 1 to 2 years. The grayling in this stage grows constantly and keeps moving on searching for abundant food sources.
- Stage 2+: The grayling is called sub-adult when its age is between 2 to 3 years. Only a small number of the individuals among the whole group migrate back to their birthplace for reproducing the offspring. The rest of the graylings keep searching for food sources and keep growing constantly. The newborn offspring start their life cycle from stage 0+ and follow the life cycle to grow up.
- Stage 3+: The graylings grow into this stage is called adult, whose age is from 3 to 4 years. At this stage, most of the graylings migrate back to their birthplace and reproduce their offspring. The rest of the

978-0-7695-4281-2/10 $26.00 © 2010 IEEE
DOI 10.1109/ICGEC.2010.198

graylings keep staying around where they are and seeking for the food sources.

- Stage 4+: This stage represents the adult graylings aged 4 to 5 years. All graylings in this stage migrate back to their birthplace for reproducing the off spring.
- The symbol, S_1, denotes the survival rate of the individuals, which grow from stage 0+ to stage 1+; S_2 indicates the survival rate of the individuals grow from stage 1+ to 2+ and so forth.
- F_2, F_3 and F_4 represent the fecundities of individuals migrating back to the birthplace and reproduce the offspring.

The parameters of the survival rate and the fecundity rate are represented by values between 0 and 1. In addition, based on the observations in literature [2], the survival rates are set to be $s_1 > s_2 > s_3 > s_4$ due to the survival rates decrease with the increase in age. Contrary to the survival rate, we set $F_2 < F_3 < F_4$ since the fecundity rate increases with the increase in age. The value of F_4 is set to be 1.0 due to we assume all the graylings must return to their birthplace for producing new offspring when they grow to the 4+ stage. F_1=0 and it is not put in Fig. 1 because the graylings in the 1+ stage are not mature and have no capacity for reproducing the offspring.

Furthermore, the energy consumption of fish swim, which is directly related to the liveliness of the fish and the food searching, is also considered. The energy consumption can be described as follows:

$$\frac{E}{t} = a + b \cdot U_s^x \tag{1}$$

where E denotes the energy consumption, t indicates the time spent to consume the energy, and U_s is the swimming speed relative to the water of the grayling, respectively; a, b, and the exponent x are all constants, which should be chosen carefully in order to make the optimization possible. The constant a is defined as the standard metabolic rate (SMR), the constant b is defined as a scaling constant denoting the rate at which energy use increases with increasing swimming speed, and the constant x is called the speed exponent describing the relationship between swimming speed and energy use [2].

Based on the findings in literature [2], the constants are chosen to $a = 2.25$, $b = 36.2$, and $x = 2.23$. With the background knowledge reviewed above, the optimization algorithm with the migration behavior of the grayling is implemented in the next session.

III. ALGORITHM DEVELOP OF THE FISH MIGRATION OPTIMIZATION

Here we define the data structure of the artificial agent, which is the grayling in this algorithm, in Eqn. 2:

$$X = < P, MP, U, eng, g > \tag{2}$$

where X indicate a grayling, P is a vector indicating the current coordinate of the grayling in the solution space, MP denotes the coordinate with the best fitness found by this grayling, U is a vector presents the current velocity of the grayling on every dimension, eng is the accumulated consumption energy, and g indicates the grow status of the grayling with $g = \{0+, 1+, 2+, 3+, 4+\}$.

To utilize the migration behavior of the fish, two processes, which we called the swim process and the migration process, are designed to achieve the optimization. The processes are described as follows:

A. Swim Process of the Fish Migration Optimization

The swim process simulates the grayling swims and grows in the water to find food sources. Finding food sources is an instinctive event of the creatures. We assume that the grayling has a few candidate spots in its mind before it swims, hence, we define a variable called Swim Candidate (*SC*), which is set $SC = 3$ in the experiments, to represent how many spots will its observe before the swimming. We make a slight change in Eqn. 1 to calculate the swim distance for making optimization in FMO. The relationship between speed, distance and time can be commonly calculated as follows:

$$d = U_s \cdot t \tag{3}$$

where d denotes the distance traveled from one spot to another in the solution space. Hence, we can substitute the variable t in Eqn. 1by Eqn. 3 to get Eqn. 4:

$$\frac{E}{d} = \left(a + b \cdot U_s^x\right) \cdot \frac{1}{U_s^{-1}} \tag{4}$$

Thus, the relationship between the swim distance and the energy consumption can be found in Eqn. 5.

$$d = \frac{E \cdot U_s}{\left(a + b \cdot U_s^x\right)} \tag{5}$$

We assume that each grayling should have different energy consumer on different dimensions to construct the offset distance for the swim process. The energy consumption on a dimension is defined as follows:

$$E_r = rand \cdot E \tag{6}$$

wehre E_r defines the energy consumed on a dimension, $rand$ is a random number in the range of $rand \in [-1, 1]$, and E is a constant defines the maxima energy consumption on a dimension. The offset distance is shown as follows:

$$d_{offset} = \frac{E_r \cdot U_s}{(a + b \cdot U_s^x)} \tag{7}$$

where d_{offset} denotes the distance moved on a dimension. Hereby the candidate spots can be calculated by adding the offset distance to the current coordinate of the grayling by Eqn. 8:

$$p_{new} = p_{old} + d_{offset} \tag{8}$$

where p_{old} denotes the coordinate of the grayling in the solution space before the swim movement, and p_{new} is the coordinate of the grayling after the swim movement.

After calculating SC coordinates of the candidate spot, evaluate the candidate spots by the fitness function to get their fitness values. Picking the candidate spot with the best fitness value for the grayling to move to and update MP by P in case the new coordinate P has better fitness value than MP . Accumulate the consumed energy over all dimensions by Eqn. (9) and then update the grow status of the grayling by Eqn. (10):

$$eng = \sum_{i=1}^{D} \left| E_{r,d} \right| \tag{9}$$

$$g = \begin{cases} \left[(g+1) \bmod 5 \right] + & \text{, if } eng > 2 \cdot E_{\max} \\ g & \text{, otherwise} \end{cases} \tag{10}$$

where D is the dimension of the solution space and $E_{\max}$ is the predefined maximum energy. Finally, update the current velocity by Eqn. (11) for the use in next iteration:

$$U = \begin{cases} 2 \cdot U_s & \text{, if } MP \text{ is updated by } P \\ U_s & \text{, otherwise} \end{cases} \tag{11}$$

B. Migration Process of the Fish Migration Optimization

The migration process indicates the grayling has group to maturity and is ready to migration back to its birthplace to reproduce the new offspring. The migration process only affects the graylings, which are selected in 2+ and 3+ stages, and all the graylings in the 4+ stage. The fecundity rate of F_2, F_3 and F_4 are set to 0.05, 0.1, and 1.0, accordingly. It results in 5% individuals in stage 2+, 10% individuals in stage 3+ and all individuals in stage 4+ are processed by the migration process. The steps of the migration process are described as follows:

Step 1. Find the maximum and the minimum value over all dimensions of the grayling by Eqn. (12) and Eqn. (13):

$$d_{\max} = \max\{P\} \tag{12}$$

$$d_{\min} = \min\{P\} \tag{13}$$

where $d_{\max}$ is the maximum value over all dimensions of the grayling, and $d_{\min}$ is the minimum value over all dimensions of the grayling.

Step 2. Update the coordinate of the grayling by Eqn. (14):

$$P = \left[r \cdot \left(d_{\max} - d_{\min} \right) + d_{\min} \right] \tag{14}$$

where r is a random number in the range $r \in [0,1]$.

Step 3. Evaluate the fitness of the grayling with the new coordinate produced after the migration and update the grayling's velocity by Eqn. (15):

$$U = \begin{cases} \pi \cdot U_s & \text{, if } F(P) \text{ is better than } F(P_{best}) \\ U_s & \text{, otherwise} \end{cases} \tag{15}$$

where π is the ratio of the circumference of a circle to its diameter, $F(P)$ denotes the fitness value of the grayling, $F(P_{best})$ is the fitness value of the near best solution found so far over all individuals, and U_s is the initial velocity.

C. The Fish Migration Optimization

Based on the life cycle of the grayling in Fig. 1, we propose the Fish Migration Optimization (FMO). The diagram of the FMO is given in Fig. 2:

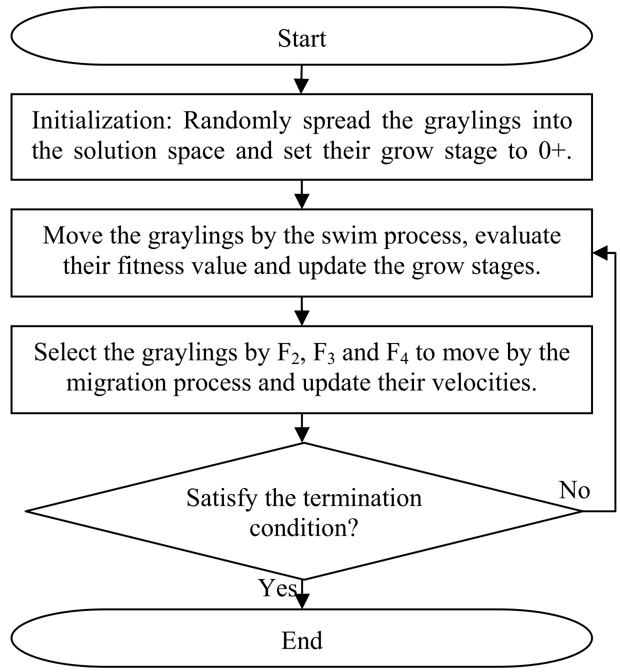

Figure 2. The diagram of the proposed FMO.

IV. Experimental Results

In order to evaluate the accuracy and the speed to find the near beset solution of the proposed FMO method, a series of experiments are taken with four familiar benchmark functions, shown as follows:

$$f_1(X) = \sum_{d=1}^{D} x_d^2 \quad \Big| \text{ Initial Range} : [-100\,100]^D \tag{16}$$

$$f_2(X) = \sum_{d=1}^{D} \frac{x_d^2}{4000} - \prod_{d=1}^{D} \cos\left(\frac{x_d}{\sqrt{d}} \right) + 1 \quad \Big| \text{ Initial Range} : [0\,600]^D \tag{17}$$

$$f_3(X) = \left\{ \begin{array}{l} -20 \exp\left(-0.2 \sqrt{\frac{1}{D} \sum_{d=1}^{D} x_d^2} \right) - \exp\left(\frac{1}{D} \sum_{d=1}^{D} \cos(2\pi x_d) \right) \\ +20 + \exp(1) \end{array} \right\} \quad \Big| \text{ Initial Range} : [-32\ \ 32]^D \tag{18}$$

$$f_4(X) = \sum_{d=1}^{D} \left(\sum_{b=1}^{d} x_b \right)^2 \quad \Big| \text{ Initial Range} : [-100\,100]^D \tag{19}$$

All benchmark functions are evaluated with 2000 iterations and repeated 25 runs. The number of dimensions of the solution space is set to 30. For both methods, the population size is set to 20. The final results are presented by average fitness value over 25 runs and the results are compared with the particle swarm optimization (PSO) method. The objective over all experiments is to minimize the outcomes of the benchmark function. The parameter setting for the PSO and the FMO is listed in Table 1:

TABLE I. PARAMETER SETTING FOR THE PSO AND THE FMO

The PSO method		The FMO method	
Parameter	Value	Parameter	Value
c_1	2.0	SC	3
c_2	2.0	F_2	0.05
Maximum velocity	30.0	F_3	0.1
		Maximum velocity	10.0
		Initial velocity	10.0

Fig. 3 shows the experimental result of the benchmark functions, where the horizontal axis is the iteration number, and the vertical axis is the fitness value. Due to the convergence of the proposed FMO method is quite fast, we only show the first 20 iterations in Fig. 3. A comparison of the experimental results of the PSO method and the FMO method are listed in Table 2:

TABLE II. A COMPARISON OF THE EXPERIMENTAL RESULTS

Function	The PSO method		The FMO method	
	Fitness value	Spent Time[a]	Fitness value	Spent Time[a]
f_1	1.996×10^{-13}	3.914×10^{-2}	0	5.135×10^{-3}
f_2	2.582×10^{2}	5.944×10^{-2}	0	7.045×10^{-3}
f_3	2.457×10^{0}	1.078×10^{-1}	4.000×10^{-16}	8.101×10^{-3}
f_4	2.933×10^{0}	7.659×10^{-2}	0	7.896×10^{-3}

a. The spent time to find the near best solution in second

V. CONCLUSION

In this paper, we proposed the fish migration optimization (FMO) method based on the observations of migrating fishes for solving optimization problems. In this paper, four benchmark functions are used to evaluate the accuracy and the convergence speed of the proposed FMO method. The experimental results show that the proposed FMO method gets higher accuracies with less computational time than the PSO method.

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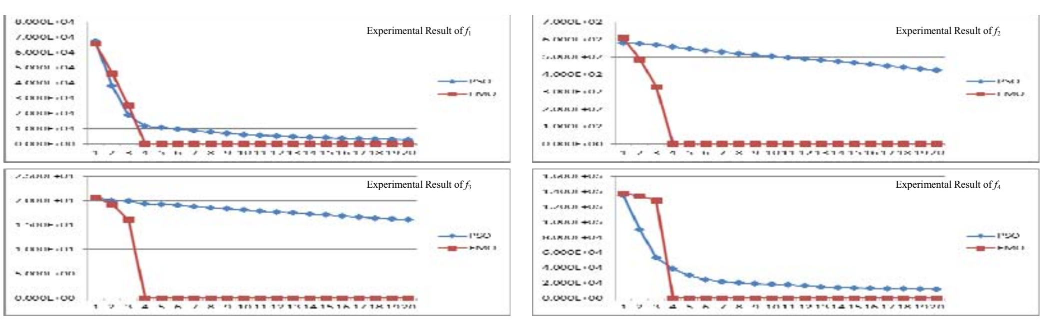

Figure 3. The experimental resulots of f_1 to f_4.