An efficient improved particle swarm optimization based on prey behavior of fish schooling

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Abstract

Particle swarm optimization (PSO) is a population based optimization technique to search approximate solutions for extremely difficult or impossible numeric problems. However, PSO may easily get trapped in a local optimum when solving complex multimodal problems. This paper proposes an efficient improved PSO based on prey behavior of fish schooling (FSPSO). Firstly, the fish find better place to prey according to the heuristic water wave which other fish provide, and the heuristic information can be used to enhance the global search ability in PSO. Therefore, the global best particle searches randomly towards several best positions that other particles have experienced. Secondly, the weak fish that cannot move quickly are eaten when the fish schooling are attacked. The decimation of the weak fish can be simulated in PSO to avoid the local optimum and to increase the diversity of the population. Hence, the particles in the immediate vicinity of the global worst particle are replaced by new particles. Finally, the proposed FSPSO is tested on both several standard benchmark functions and a typical NP-complete problem. The results demonstrate that our algorithm achieves remarkable improvements over the basic PSO and even other improved PSOs.

Key words : Improved particle swarm optimization, Fish schooling, Prey behavior, Global search ability, Local optimum

1. Introduction

The particle swarm optimization is a parallel evolutionary computation technique developed by Kennedy and Eberhart based on the social behavior of bird flocking (Kennedy and Eberhart, 1995; Tang, et al., 2014). PSO is very popular due to its simplicity of implementation and ability to quickly converge to a reasonably good solution. Therefore, PSO is applied to a wide range of problems, including logistics optimization (Yoshiaki, et al., 2014), fault diagnosis (Zhu, et al., 2014), parameter optimization (Marko, et al., 2014; Duan and Hao, 2014), graphics, image, CAD (Wen, et al., 2015; Qi, 2014; Chang, et al., 2014; Huang, et al., 2011; Liu, et al., 2011; Li, et al., 2013; Cheng, et al., 2013), and flowshop scheduling problems (Zhang, et al., 2008; Liao, et al., 2007)

However, PSO may easily get trapped in a local optimum when solving complex multimodal problems (Liang, et al., 2006). Many attempts have been made to improve the performance of PSO, such as inertia weight is changed with iterations, adjusted neighborhood is searched and other search techniques are combined with PSO (Angeline, 1998; Liu, et al., 2005). Eberhart found a significant improvement in the performance with a linearly varying inertia weight over the generations (Hu and Eberhart, 2002). The randomized inertia weight, nonlinear inertia weight (Chatterjee and Siarry, 2006) and dynamically changing inertia weight (Yang, et al., 2007) were proposed. Kennedy claimed that PSO with a small neighborhood might perform better on complex problems, while PSO with a large neighborhood would perform better on simple problems (Kennedy, 1999). Suganthan applied a dynamically adjusted neighborhood where the neighborhood of a particle gradually increased until it included all particles (Suganthan, 1999).

To enhance the performance, the improved PSOs that are combined with other search techniques have been studied by some researchers (Shelokar, et al., 2007). Evolutionary operators such as selection, crossover, and mutation have been introduced to the PSO to keep the best particles (Shi, et al., 2003). The swarm is divided into subpopulations, and a breeding operator is used within a subpopulation or between the subpopulations to increase the diversity of the population (Lovbjerg, et al., 2001). Negative entropy is used to discourage premature convergence (Xie, et al., 2002). PSO combined with chaos is proposed (Alatas, et al., 2009; Jiang and Bompard, 2005). Higashi and Iba present PSO with gaussian mutation (Higashi and Iba, 2003). Wang and Li integrate PSO and simulated annealing to improve the performance of PSO (Wang and Li, 2004). Hieu and Hiroshi propose a new PSO using differential evolution (DE) with genetic algorithm (GA) to reduce calculation cost and to improve convergence towards the optimal solution (Hieu and Hiroshi, 2013).

The paper proposes an improved particle swarm optimization based on prey behavior of fish schooling, which is different from the social behavior in many references (Neshat, et al., 2012; Yao, et al., 2010). The motivation behind our algorithm is the intelligent prey behavior of fish schooling. The fish find better place to prey according to the heuristic water wave provided by other fish. To imitate the behavior, the global best particle searches randomly towards several best positions that other particles have experienced. The weak fish that cannot move quickly are eaten when the fish schooling are attacked. To simulate the behavior, the particles in the immediate vicinity of the global worst particle are replaced by new particles.

This paper is organized as follows. In Section 2, FSPSO is presented and described. In Section 3, the performance of FSPSO is analyzed by experiments. Finally, conclusions are summarized in Section 4.

2. Improved particle swarm optimization based on prey behavior of fish schooling

2.1. Basic particle swarm optimization

In basic PSO, the i th particle has a current position X_i and a current velocity V_i , then:

$$X_i = (X_{i1}, \dots, X_{id}, \dots, X_{iD}) \quad (1)$$

$$V_i = (V_{i1}, \dots, V_{id}, \dots, V_{iD}) \quad (2)$$

where D is the search space dimension, $1 \leq i \leq n$, $1 \leq d \leq D$. $P_i = (P_{i1}, P_{i2}, \dots, P_{iD})$ is the best position that the i th particle have experienced. $P_g = (P_{g1}, P_{g2}, \dots, P_{gD})$ is the global best position among all the particles (Liu, et al., 2010). Then the evolution equation of PSO is:

$$V_{id}^{k+1} = wV_{id}^k + c_1r_1(P_{id}^k - X_{id}^k) + c_2r_2(P_{gd}^k - X_{id}^k) \quad (3)$$

$$X_{id}^{k+1} = X_{id}^k + V_{id}^{k+1} \quad (4)$$

where w is inertia weight, c_1 and c_2 are learning coefficients, r_1 and r_2 are two separately generated uniformly distributed random numbers in the range $[0, 1]$, k is the iteration number. The first part of Eq. (3) represents the previous velocity, which provides the necessary momentum for particles to roam across the search space. The second part, known as the cognitive component, represents the personal thinking of each particle. The third part is known as the social component, which represents the collaborative effect of the particles, in finding the global optimal solution (Ratnaweera, et al., 2004).

2.2. Prey behavior of fish schooling

It has been investigated that complex pressure waves and other water movements are used by fish schooling as communication methods in prey behavior (Larsson, 2009). The fish will find better place to prey according to the heuristic water wave. Therefore, the water wave can be viewed as heuristic information in PSO. In the prey process, the fish schooling will be attacked by other predators. In the darwinian world of fish schooling, the weak fish that cannot move quickly will be eaten (Ota, et al., 2003). The survival of the fittest is the law of nature (Patel, 2002). Hence, elimination of the weak particles in PSO can improve the the fitness of the population.

In this paper, FSPSO simulates the prey behavior of fish schooling to improve the performance. To enhance the global search ability, the global best particle searches randomly towards several best positions that other particles have experienced. To avoid the local optimum and to increase the diversity of the population, the particles in the immediate vicinity of the global worst particle are replaced by random particles.

2.3. Improve the global best position

The fish find better place to prey according to the heuristic information provided by other fish. To imitate the behavior in PSO, the global best particle should search to new directions according to the heuristic information that m other particles provide, hoping that the search processing will lead to find better position than the global best one.

Without loss of generality, the m particles are chosen randomly, and the best positions that the m particles have experienced are $P_1, P_2, \dots, P_m$. Then the directions that the global best particle searches are shown in Fig. 1.

Since we select the new directions from a limited set specialized by the best positions of the m particles, our algorithm is different from local search method, which will search the neighbour space.

Fig. 1 Directions the global best particle searches

As shown in Fig. 1, the global best particle searches randomly towards several best positions that the m particles have experienced, and P_1, P_2, P_j, P_m are the positions that the global best particle searches towards. Then the position of the j th direction that the global best particle searches is as follows:

$$XX_j = P_g + r_3 \bullet c_3 \bullet (P_j - P_g) \quad (5)$$

where $1 \leq j \leq n$, r_3 is a random number uniformly distributed in the range $[0, 1]$, c_3 is the search coefficient. If the best position in XX_j is better than P_g , P_g is replaced by the best position. Then the global search ability of FSPSO can be enhanced.

2.4. Improve particles in the immediate vicinity of the global worst particle

The weak fish that cannot move quickly are eaten when the fish schooling are attacked. To simulate the behavior, the weak particles are replaced by new particles that are generated randomly. In our algorithm, the particles in the immediate vicinity of the global worst particle are the weak particles.

Without loss of generality, the position of the global worst particle is $P_b = (P_{b1}, P_{b2}, \dots, P_{bD})$, the position of the j th weak particle is Y_j , and the distance between Y_j and P_b is short. Then the relationship of Y_j and P_b is shown in Fig. 2.

As shown in Fig. 2, Y_1, Y_2, Y_j are the weak particles, and they are in the circle, then:

$$\sum_{i=1}^D |Y_{ji} - P_{bi}| \leq c_4 \bullet Range \quad (6)$$

where $Range$ is the search range of particles, c_4 is the range coefficient. The weak particles in the immediate vicinity of P_b are replaced by random particles. Therefore, the diversity of the population is increased and FSPSO can avoid the local optimum.

Fig. 2 The particles in the immediate vicinity of the global worst particle

2.5. The step of FSPSO

FSPSO that simulates the prey behavior of fish schooling is proposed. The steps of FSPSO are as follows:

Step 1: The parameters of FSPSO are initialized. The individual number n , the maximum iteration number $maxk$, inertia weight w , learning coefficients c_1 and c_2 , search coefficient c_3 and range coefficient c_4 are initialized.

Step 2: The position and velocity of the particle are updated according to Eq. (3) and Eq. (4).

Step 3: The global best position is improved according to Eq. (5).

Step 4: The particles in the immediate vicinity of the global worst particle are improved according to Eq. (6).

Step 5: If the termination condition of FSPSO is satisfied, output the position of the global best particle which is the solution of the optimization problem; otherwise, turn to Step 2.

2.6. The complexity analysis of FSPSO

In FSPSO, the maximum iteration number is $maxk$. It takes $O(n * D)$ to compute the position of each particle's own personal best position P_i , the global best position P_g and the global worst position P_b . It takes $O(n * D)$ to replace the particles in the immediate vicinity of the global worst particle with random particles. The time complexity that the global best particle searches better position is $O(m)$. As m is small, then the time complexity of FSPSO is $O(n * D * maxk)$. In FSPSO, P_i , P_g and P_b should be preserved. Then the space complexity of FSPSO is $O(n * D)$. Therefore, the space and time complexity of FSPSO are the same as those of PSO, and the performance of FSPSO is high.

3. The analysis of experiment

3.1. Function optimization

In order to evaluate the performance of FSPSO, the algorithm is applied to optimize several standard benchmark functions (Van den Bergh and Engelbrecht, 2004; Rashedi, et al., 2009; Li, et al., 2013; Eckart, et al., 2000). The experiment environment is as follows: CPU: i7-2600k @3.4GHz; physical memory: 8GB; software: Matlab 2013b. The benchmark functions are in Table 1.

Table 1 Benchmark functions

Function	Range
$f_1(x) = \sum_{i=1}^N x_i^2$	[-100, 100]
$f_2(x) = \sum_{i=1}^N x_i + \prod_{i=1}^N x_i $	[-10, 10]
$f_3(x) = \sum_{i=1}^N (\sum_{j=1}^N x_j)^2$	[-100, 100]
$f_4(x) = \max_i \{ x_i , 1 \leq i \leq N\}$	[-100, 100]
$f_5(x) = \sum_{i=1}^{N-1} (100(x_{i+1} - x_i^2)^2 + (x_i - 1)^2)$	[-30, 30]
$f_6(x) = \sum_{i=1}^N (x_i + 0.5)^2$	[-100, 100]
$f_7(x) = \sum_{i=1}^N (x_i^2 - 10 \cos(2\pi x_i) + 10)$	[-5.12, 5.12]
$f_8(x) = -20 \exp(-0.2 \sqrt{\frac{1}{N} \sum_{i=1}^N x_i^2}) - \exp(\frac{1}{N} \sum_{i=1}^N \cos(2\pi x_i)) + 20 + e$	[-32, 32]
$f_9(x) = \sum_{i=1}^N \frac{x_i^2}{4000} - \prod_{i=1}^N \cos(\frac{x_i}{\sqrt[4]{i}})$	[-600, 600]

$f_1(x) - f_6(x)$ are unimodal functions and $f_7(x) - f_9(x)$ are multimodal functions. In these functions, N is the dimension of the function, the minimum value (f_{min}) of the functions are zero, and the optimum location (X_{opt}) for functions are in $[0]^N$. FSPSO is applied to optimize these functions as well as PSO and GA. Then the results are compared to evaluate the performance of FSPSO. In the three algorithms, the dimension is 30 ($N=D=30$), population is 50 and maximum iteration number is 1000. In PSO, $c_1 = c_2 = 2$, inertia factor (w) is decreasing from 0.9 to 0.7 linearly with the iterations. Compared experiments are made to find the appropriate values of parameters in FSPSO and the results are as follows: $c_3=1.5$, $c_4=0.0001$, $m=6$, and other parameters are set as the same as PSO. The parameters of GA are set as follows: single point uniform crossover with the rate of 0.95, random selection mechanism, gaussian mutation with the rate of 0.1 (Karaboga and Basturk, 2008). All experiments run 30 times. The best, average, median and variance values of the solutions obtained by GA, PSO and FSPSO are given in Table 2.

Table 2 Function optimization results obtained by the GA, PSO and FSPSO

Function	Algorithm	Best	Average	Median	Variance
$f_1(x)$	GA	0.14592	0.63625	0.58375	0.41057
	PSO	0.002427	2.7357	0.68436	3.6599
	FSPSO	0.002104	2.1229	0.57377	2.946
$f_2(x)$	GA	1.2841	3.2947	3.2745	1.4063
	PSO	0.019645	0.73631	0.6005	0.69595
	FSPSO	0.006164	0.56639	0.32647	0.63668
$f_3(x)$	GA	1.1849	3.8748	3.2517	1.8998
	PSO	0.94601	1100.9	623.68	1562.3
	FSPSO	0.006776	407.19	135.98	613.01
$f_4(x)$	GA	0.57362	0.71238	0.71985	0.094686
	PSO	0.01335	0.18487	0.17502	0.14434
	FSPSO	0.012606	0.17555	0.13542	0.08965
$f_5(x)$	GA	0.43722	100.49	112.73	51.818
	PSO	0.000707	17.702	9.7506	19.366
	FSPSO	0.000623	8.8467	3.3622	10.234
$f_6(x)$	GA	0.081631	1.1758	0.68473	2.0158
	PSO	0.001161	1.0023	0.14625	1.6907
	FSPSO	0.000173	1.0008	0.1364	1.6649
$f_7(x)$	GA	2.8672	12.977	11.281	7.313
	PSO	0.000286	0.48013	0.096227	0.8008
	FSPSO	0.000107	0.42118	0.12176	1.2556
$f_8(x)$	GA	0.28697	1.2358	1.2599	0.42428
	PSO	0.034773	3.2062	3.4702	2.3946
	FSPSO	0.000107	2.8061	3.3161	1.9283
$f_9(x)$	GA	0.029616	0.063848	0.058647	0.022878
	PSO	0.01908	0.61927	0.57628	0.38699
	FSPSO	0.013158	0.04613	0.03821	0.01732

As shown in Table 2, the best values obtained by FSPSO are better than those obtained by GA and PSO for all functions. Then the global search ability of FSPSO is better. The average values obtained by FSPSO are better than those obtained by PSO for all functions, and the average values obtained by FSPSO are better than those obtained by GA besides $f_1(x)$, $f_3(x)$ and $f_8(x)$. Then the whole search ability of FSPSO is better. The median values obtained by FSPSO are smaller than those obtained by PSO besides $f_7(x)$, and the median values obtained by FSPSO are smaller than those obtained by GA besides $f_3(x)$ and $f_8(x)$. The variance values obtained by FSPSO are smaller than those obtained by PSO except for $f_7(x)$, and the variance values obtained by FSPSO are smaller than those obtained by GA except for $f_1(x)$, $f_3(x)$ and $f_8(x)$. Then the stability of FSPSO is better.

The best values of the solutions obtained by the three algorithms for benchmark functions are compared in Fig. 3. To compare distinctly, the best values are taken logarithm.

As shown in Fig. 3, the best values of the solutions obtained by FSPSO is smaller than those obtained by other algorithms, and the global search ability is stronger. The convergence curves are used to evaluate the performance of GA, PSO and FSPSO. A random unimodal function $f_2(x)$ and a random multimodal function $f_7(x)$ are chosen to be optimized by these algorithms. To analyze the convergence curves better, the fitness values in the iteration are taken logarithm. The convergence curves of the three algorithms for the functions are shown in Fig. 4 and Fig. 5.

According to these figures, FSPSO has better search ability and convergence for the two functions. FSPSO tends to find the global optimum faster and hence has a higher convergence rate. Compared to PSO, FSPSO is more efficient. Therefore, FSPSO shows remarkable improvements to optimize the benchmark functions.

Fig. 3 Best values for benchmark functions

Fig. 4 Convergence curves for $f_2(x)$

Fig. 5 Convergence curves for $f_7(x)$

3.2. Knapsack problem

The knapsack problem is a typical NP-complete problem. The GA, PSO and FSPSO are used to optimize a knapsack problem (Sinha and Zoltners, 1979; Martello, et al., 2000; Chen and Ross, 2014; Chu and Beasley, 1998; Zhao and Li, 2014). The parameters of three algorithms and the experiment environment are the same as those in function optimization. The value matrix C and volume matrix W are as follows:

$$C = \begin{pmatrix} 220 & 208 & 198 & 192 & 180 & 180 & 165 & 162 & 160 & 158 \\ 155 & 130 & 125 & 122 & 120 & 118 & 115 & 110 & 105 & 101 \\ 100 & 100 & 98 & 96 & 95 & 90 & 88 & 82 & 80 & 77 \\ 75 & 73 & 72 & 70 & 69 & 66 & 65 & 63 & 60 & 58 \\ 56 & 50 & 30 & 20 & 15 & 10 & 8 & 5 & 3 & 1 \end{pmatrix} \quad (7)$$

$$W = \begin{pmatrix} 80 & 82 & 85 & 70 & 72 & 70 & 66 & 50 & 55 & 25 \\ 50 & 55 & 40 & 48 & 50 & 32 & 22 & 60 & 30 & 32 \\ 40 & 38 & 35 & 32 & 25 & 28 & 30 & 22 & 50 & 30 \\ 45 & 30 & 60 & 50 & 20 & 65 & 20 & 25 & 30 & 10 \\ 20 & 25 & 15 & 10 & 10 & 10 & 4 & 4 & 2 & 1 \end{pmatrix} \quad (8)$$

The limited volume is 1000. As knapsack problem is a discrete problem, then the position of each particle i is defined as:

$$X_{id}^k = \begin{cases} 1 & \text{if } r_4 < \text{sig}(V_{id}^k) \\ 0 & \text{else} \end{cases} \quad (9)$$

where $\text{sig}(V_{id}^k) = \frac{1}{1+\exp(-V_{id}^k)}$, r_4 is a random number uniformly distributed in the range [0, 1]. The convergence curves of the three algorithms for the knapsack problem are in Fig. 6.

Fig. 6 Convergence curves for the knapsack problem

As shown in Fig. 6, the global best value of FSPSO is greater than those obtained by other algorithms, and the global search ability is stronger. The three algorithms run 30 times to optimize the knapsack problem. The best, worst, average, median and variance values of the best solutions obtained by the GA, PSO and FSPSO are given in Table 3.

Table 3 Knapsack problem optimization results obtained by the GA, PSO and FSPSO

Algorithm	Best	Worst	Average	Median	Variance
GA	2909	2670	2788.5	2787	49.5
PSO	2955	2687	2820.3	2812	58.7
FSPSO	3030	2899	2957.4	2961	31.8

As shown in Table 3, the best, worst, average and median values obtained by the FSPSO are greater than the corresponding values obtained by the GA and PSO, and the variance value obtained by the FSPSO is smaller. Thus, the global search ability and convergence of the FSPSO are better than those of the other two algorithms, indicating that the FSPSO is more efficient for solving the knapsack problem.

3.3. Further analysis of FSPSO in function optimization

The main concepts of FSPSO are improvement of the global best position and elimination of the weak particles. Then their performances are compared individually to optimize the benchmark function $f_1(x)$. Algorithm1 is PSO combined with improvement of the global best position and Algorithm2 is PSO combined with elimination of the weak particles.

We also compare our algorithm with other improved PSOs, particularly with the PSO using improved global best position, such as the improved PSO combined with local search (Wu, 2014), which is named LSPSO in this paper. The comparison results are in Fig. 7, and the fitness values are taken logarithm

Fig. 7 Further analysis of FSPSO

As shown in Fig. 7, the solution quality of both Algorithm1 and Algorithm2 are improved compared to basic PSO. So, the individual effectiveness of our idea, improvement of the global best position and elimination of the weak particles, are confirmed. And the solution quality of FSPSO is the best one among the five algorithms.

The runtimes of PSO, Algorithm1, Algorithm2, LSPSO and FSPSO are 1.85, 2.28, 1.91, 2.72 and 2.34 seconds, respectively. In future work, we will extend our FSPSO in parallel computation architecture to reduce computation time while keep the solution quality.

According to Fig. 7, the runtime of FSPSO is little longer than that of basic PSO. However, the runtime difference is acceptable when considering that the solution quality of FSPSO is much better than that of basic PSO.

According to Fig. 7, both the solution quality and runtime of FSPSO are better than those of LSPSO, so our FSPSO can outperform other improved PSOs.

4. Conclusion

An efficient improved particle swarm optimization based on prey behavior of fish schooling is presented in the paper. The global best particle searches randomly towards several best positions that other particles have experienced, therefore the global search ability becomes stronger in FSPSO. The particles in the immediate vicinity of the global worst particle are replaced by random particles, therefore the diversity of the population is increased and the local optimum is efficiently avoided in FSPSO. The proposed algorithm has been tested to optimize several standard benchmark functions and a typical NP-complete problem. The obtained results confirm the high performance of FSPSO in solving the continuous and discrete optimization problems. In future work, we will extend FSPSO in both parallel computing methods such as multi-core CPU/GPU/APU architectures and applications such as collaborative design of embedded hardware/software partition.

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