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An improved artificial fish swarm algorithm optimized by particle swarm optimization algorithm with extended memory

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Abstract

Purpose – The purpose of this paper is to solve the problem that the standard particle swarm optimization (PSO) algorithm has a low success rate when applied to the optimization of multi-dimensional and multi-extreme value functions, the authors would introduce the extended memory factor to the PSO algorithm. Furthermore, the paper aims to improve the convergence rate and precision of basic artificial fish swarm algorithm (FSA), a novel FSA optimized by PSO algorithm with extended memory (PSOEM-FSA) is proposed.

Design/methodology/approach – In PSOEM-FSA, the extended memory for PSO is introduced to store each particle' historical information comprising of recent places, personal best positions and global best positions, and a parameter called extended memory effective factor is employed to describe the importance of extended memory. Then, stability region of its deterministic version in a dynamic environment is analyzed by means of the classic discrete control theory. Furthermore, the extended memory factor is applied to five kinds of behavior pattern for FSA, including swarming, following, remembering, communicating and searching.

Findings – The paper proposes a new intelligent algorithm. On the one hand, this algorithm makes the fish swimming have the characteristics of the speed of inertia; on the other hand, it expands behavior patterns for the fish to choose in the search process and achieves higher accuracy and convergence rate than PSO-FSA, owning to extended memory beneficial to direction and purpose during search. Simulation results verify that these improvements can reduce the blindness of fish search process, improve optimization performance of the algorithm.

Research limitations/implications – Because of the chosen research approach, the research results may lack persuasion. In the future study, the authors will conduct more experiments to understand the behavior of PSOEM-FSA. In addition, there are mainly two aspects that the performance of this algorithm could be further improved.

Practical implications – The proposed algorithm can be used to many practical engineering problems such as tracking problems.

Social implications – The authors hope that the PSOEM-FSA can increase a branch of FSA algorithm, and enrich the content of the intelligent algorithms to some extent.

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Originality/value – The novel optimized FSA algorithm proposed in this paper improves the convergence speed and searching precision of the ordinary FSA to some degree.
Keywords Optimization techniques, Algorithms, Artificial intelligence, Simulation
Paper type Research paper

1. Introduction

Particle swarm optimization (PSO) algorithm is an evolutionary computation technique proposed by Kennedy and Eberhart (1995). It mimics the behavior of flying birds and their communication mechanism to solve optimization problems, and is based on a constructive cooperation between particles in contrast to survival of the fittest approach used in other evolutionary methods. Usually, PSO algorithm has many advantages. Therefore algorithm has gained popularity recently (Banks *et al.*, 2007, 2008; Song *et al.*, 2012; Wang *et al.*, 2013; Yang *et al.*, 2006; Zhang *et al.*, 2007) and found applications in many practical engineering problems (Banks *et al.*, 2007, 2008; Song *et al.*, 2012).

Fish swarm algorithm (FSA) is a stochastic population-based algorithm motivated by intelligent collective behavior of fish groups in nature (Li *et al.*, 2002). FSA have some advantages, such as non-sensitive initial artificial fish location, flexibility and fault tolerance (Reza, 2014). It has been applied into different problems including machine learning (Yazdani *et al.*, 2010; Hu *et al.*, 2010), PID controlling (Luo *et al.*, 2010), wireless sensor networks (Song *et al.*, 2010) and scheduling (Bing and Wen, 2010). Both of FSA and PSO algorithm are swarm intelligence algorithms (Li *et al.*, 2002), which are used for simulating natural or social behavior (Eberhart and Kennedy, 1995). Although these algorithms respectively possess different advantages, some issues should be further improved and optimized, such as the convergence speed and optimization precision of the algorithms. For example, Song *et al.* (2013) proposed an improved FSA by enlarging the visual field gradually according to the iteration and applied the improved algorithm to a two-dimensional cutting stock problem. Huang and Chen (2013) established an improved artificial FSA based on hybrid behavior selection in order to deal with the problem that there has no general research theory to select behaviors of fishes presently. Zhang *et al.* (2014) presented an improved artificial FSA by introducing the idea of interactive learning between individual historical optimization and that of the global one as well as improving the update strategy for artificial fish's position.

What's more, the extended memory was introduced to store each particles' historical information consisting of recent positions, personal and global best positions in the PSOEM algorithm (Duan *et al.*, 2011). Moreover, the parameter (ξ_{t-1}) is used to describe the importance of extended memory. Since PSOEM algorithm and PSO algorithm were homologous but heterogeneous in structure, PSOEM algorithm could integrate with the numerous existing improved PSO algorithms and combined respective advantages (Duan *et al.*, 2011). Furthermore, FSA was optimized by PSOEM algorithm, and then a novel intelligent search algorithm called PSOEM-FSA is put forward. On the one hand, this algorithm makes the fish swimming be provided with the characteristic of the speed inertia; on the other hand, it expands the behavior patterns with extended memory for the fish to choose in the searching process and achieves higher searching precision and convergence speed in comparison with PSO-FSA (Duan *et al.*, 2013). Numerical simulation experiments are done to verify the performance of the proposed algorithm in this paper.

The remainder of the paper is organized as follows: in Section 2, the proposed PSOEM-FSA, standard PSO algorithm, PSOEM algorithm and the specific process and the flowchart of PSOEM-FSA are introduced. Furthermore, the proposed PSOEM-FSA and the specific process and the flowchart of PSOEM-FSA are described in Section 3. Then, numerical simulation experiments and discussion are carried out and high performance of PSOEM-FSA is demonstrated in Section 4. Finally, the conclusion and future work are proposed in Section 5.

2. Preliminaries of PSO

As stated above, the main objective of this paper is to assess the contribution of merging the extended memory and PSO algorithm into FSA for the optimization problems. The two key components of the proposed algorithm are PSOEM (Duan *et al.*, 2011) and the improved fish behavior patterns. In the following subsection, we will detail them and explain how they work together seamlessly.

2.1 The standard PSO

The standard PSO is shown as follows:

$$v_{t+1} = \omega v_t + \alpha_t^l \left(p_t^l - x_t\right) + \alpha_t^g \left(p_t^g - x_t\right) \tag{1}$$

$$x_{t+1} = x_t + v_{t+1} \tag{2}$$

where subscript t denotes the index of iteration; v_t represents the speed of the particle in the tth iterative process; x_t represents the particle' speed in the tth iterative process; p_t^l represents the current individual extreme value point of the particle in the tth iterative process; p_t^g represents the current global extreme value point of the population in the tth iterative process; ω is known as the inertia weight; c_1 and c_2 are treated as the acceleration factors, and $a_t^l = c_1 r_1$, $a_t^g = c_2 r_k$, $r_1, r_2 \sim U(0, 1)$, $\omega, a_t^l, a_t^g \in R$, $a_t^l \sim U(0, c_1)$, $a_t^g \sim U(0, c_2)$.

2.2 Improved PSO

Recently, the various kinds of improved PSO algorithms have been presented in order to further improve the optimization performance. For example, PSOEM combines several improved PSO algorithms, making full use of their advantages (Duan *et al.*, 2011). From a psychological point of view, expanded memory means that the individual accumulates the search experience, which is conducive to improve the convergence speed. PSOEM can be expressed as follows:

$$\begin{aligned} v_{t+1} = \omega v_t &+ \alpha_t^l \left[\xi_t \left(p_t^l - x_t\right) + \xi_{t-1} \left(p_{t-1}^l - x_{t-1}\right)\right] \\ &+ \alpha_t^g \left[\xi_t \left(p_t^g - x_t\right) + \xi_{t-1} \left(p_{t-1}^g - x_{t-1}\right)\right] \end{aligned} \tag{3}$$

where p_{t-1}^l represents current extreme value point of the particle in the $t-1$th iterative process; p_{t-1}^g represents the current global extreme value point of the population in the $t-1$th iterative process, ξ_t is called current effective factor; ξ_{t-1} is called the effective factor of extended memory, and $x_{t+1} = x_t + v_{t+1}$, ξ_t, $\xi_{t-1} \in R^+$, $\sum \xi_i = 1$. In particular, when $\xi_{t-1} = 0$, that is, $\xi_t = 1$, then (3) = (1). In this sense, PSO algorithm can be considered as a special case of PSOEM.

3. Proposed algorithm

Being attracted by the potential of FSA, a lot of improved algorithms based on the ordinary FSA have been proposed, such as the introduction of taboo optimization operator (Yu *et al.*, 2005), the introduction of the fish jumping behavior (Wang *et al.*, 2005), as well as the introduction of fish memory behavior (Tsai and Lin, 2011). In the proposed algorithm, the various characteristics of PSOEM algorithm, including speed inertia, the memory (learning) of individual particle, and information exchange and sharing between particles, respectively are introduced into the FSA, and then PSOEM-FSA is put forward. The improvements of the proposed algorithm are expressed as follows.

At first, the speed parameter is introduced into each of the artificial fishes (Duan *et al.*, 2013). Taking the swarm behavior, for example, the updated speed formula can be represented as follows:

$$V_{t+1} = \omega V_{\mathrm{t}} + rand \times \frac{Step \times \left(X_t^c - X_t\right)}{norm\left(X_t^c - X_t\right)} \tag{4}$$

where ω is the inertia weight; v_t represents the velocity vector of the artificial fish in the tth iterative process; Step is the largest mobile step length; X_t^c is the center of the cluster behavior vector; X_t represents the current position vector of the artificial fish in the tth iterative process; $norm\left(X_t^c - X_t\right)$ represents the distance between the two position vector, and $rand \sim U$ (0, 1).

Second, the memory behavior pattern is introduced. This behavior makes the artificial fish in swimming refer to its own optimal position, which can reduce the blindness of the fish in the search process. The updated speed is shown as follows:

$$V_{t+1} = \omega V_{\mathrm{t}} + rand \times \frac{Step \times \left[\xi_t\left(X_t^{pbest} - X_t\right) + \xi_{t-1}\left(X_{t-1}^{pbest} - X_{t-1}\right)\right]}{norm\left[\xi_t\left(X_t^{pbest} - X_t\right) + \xi_{t-1}\left(X_{t-1}^{pbest} - X_{t-1}\right)\right]} \tag{5}$$

where X_t^{pbest} represents the optimal position vector of the artificial fish on the bulletin board in the tth iterative process; X_{t-1}^{pbest} represents the optimal position vector of the artificial fish on the bulletin board in the $t-1$th iterative process.

Third, the communication behavior pattern is introduced. This behavior makes the artificial fish in swimming refer to the optimal position of the whole fish, which strengthens the ability of exchanging and sharing information between the individual in the search process, and further reduces the blindness of the fish in the search process. The updated velocity is shown as follows:

$$V_{t+1} = \omega V_{\mathrm{t}} + rand \times \frac{Step \times \left[\xi_t\left(X_t^{gbest} - X_t\right) + \xi_{t-1}\left(X_{t-1}^{gbest} - X_{t-1}\right)\right]}{norm\left[\xi_t\left(X_t^{gbest} - X_t\right) + \xi_{t-1}\left(X_{t-1}^{gbest} - X_{t-1}\right)\right]} \tag{6}$$

where X_t^{gbest} represents the current global extreme value point of the population on the bulletin board in the tth iterative process; X_{t-1}^{gbest} represents the current global extreme value point of the population on the bulletin board in the $t-1$th iterative process.

Vision and step length are two very important parameters for FSA, and have important effect on the optimization result. In this paper, we dynamically define the maximum distance as vision and step length of the fish, which make two random fishes may appear to be in the D dimension search space. Furthermore, we define the maximum distance as the MaxD given by formula (7) (Duan *et al.*, 2013):

$$MaxD = \sqrt{(x_{max} - x_{min})^2 \times D} \quad (7)$$

where x_{max} and x_{min}, respectively represent the upper and lower bound of the optimization range; Visual is set to the linear gradient from MaxD to 0.01 MaxD; Step is set to the linear gradient from MaxD/5 to 0.

The specific process of PSOEM-FSA is shown as follows:

(1) initialize the position and speed of the fish, the optimal locations of each fish's memory and the optimal position parameters recorded on bulletin board;

(2) test the four kinds of combination behavior patterns: cluster or foraging, collision or foraging, memory or foraging and communication or foraging;

(3) select the optimal combination behavior model from Step (2) and use the velocity update current location of the artificial fish; and

(4) if the specified number of iterations is available, the optimization will end, otherwise going to Step (2).

Furthermore, the flowchart of the proposed algorithm is as follows (Figure 1).

4. Experimental results

To evaluate and analyze the performance of the proposed algorithm, we perform numerical simulation with Matlab7.1. A number of numerical simulation experiments are done to compare the performance of PSOEM-FSA with the other algorithm's, including PSO algorithm (Banks *et al.*, 2007), FSA (Li *et al.*, 2002) and PSO-FSA (Duan *et al.*, 2013), under the same parameter settings.

4.1 Numerical simulation analysis

Numerical simulation analysis is made up of optimization precision analysis, volatility analysis of optimal results, algorithm complexity analysis and simulation analysis of fish behavior patterns. Detailed experimental analysis process is as follows.

4.1.1 Experimental settings. Experiments are performed on four benchmark functions that are often used as measurement criteria of optimization algorithms in continuous and static spaces. Benchmark functions with their optimum value and optimum range are presented in Table I (Zhan *et al.*, 2009). It should be noted that optimal value of all these function equals zero. In addition, sphere function is a single-peak function, and the others are multi-peak functions. They are used to investigate the effect of PSOEM-FSA, PSO algorithm, FSA, and PSO-FSA.

To make a fair comparison among PSO (Banks *et al.*, 2007), FSA (Reza, 2014), PSO-FSA (Duan *et al.*, 2013) and PSOEM-FSA, these algorithms adopt the parameter settings in Table II. Furthermore, all algorithms run 50 times independently and are stopped when the maximum number of 1,000 function evaluations (FES).

4.1.2 Experiments of optimization precision analysis. To vividly describe the advantage of PSOEM-FSA, the convergence graphs of four test functions are plotted in Figure 2, where the abscissa represents iterations, and the vertical axis represents the average optimization results, of which the value is respectively taken by log10.

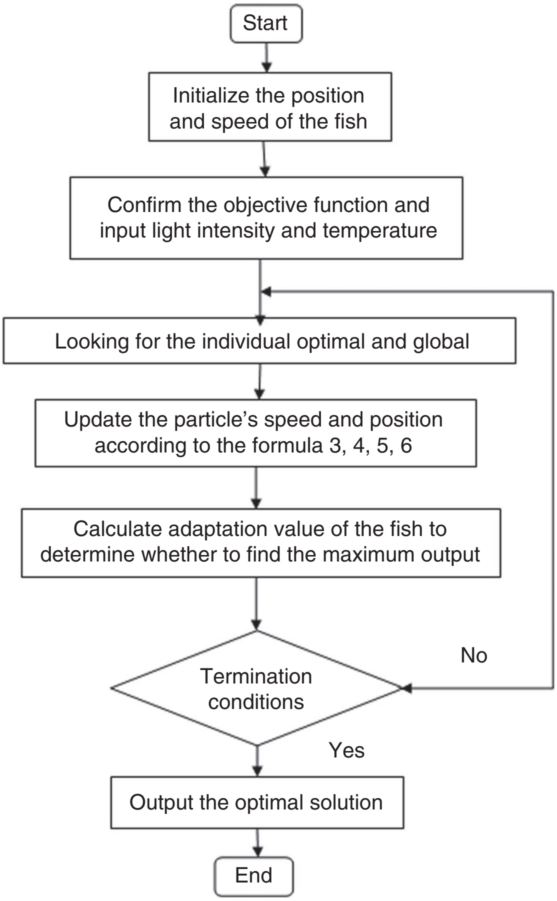

Figure 1. Flowchart of PSOEM-FSA

Table I. Benchmark test functions

Function	Expression	Optimum value	Optimal range
Sphere	$f(x) = \sum_{i=1}^{n} x_i^2$	0	$(-100, 100)^D$
Rosenbrock	$f(x) = \sum_{i=1}^{D-1} 100\left(x_{i+1}-x_i^2\right)^2+(1-x_i)^2$	0	$(-2.048, 2.048)^D$
Quadric	$f(x) = \sum_{i=1}^{D}(\sum_{j=1}^{i} x_j)^2$	0	$(-100, 100)^D$
Ackley	$f(x) = -20\exp(-0.2\sqrt{\frac{1}{D}\sum_{i=1}^{D} x_i^2})-\exp(\frac{1}{D}\sum_{i=1}^{D} \cos(2\pi x_i))+20+e$	0	$(-32.768, 32.768)^D$

Some insightful conclusions can be drawn from Table III. Table III shows the best, the average, and the log values of the average of the optimization results obtained by each algorithm for four benchmark functions under the budgeted FES over 50 independent runs. For clarity, the results of the best algorithms are marked in italics.

From Figure 2, it is clear that PSOEM-FSA consistently outperforms the other compared methods in the majority of the test functions. In addition, although PSOEM-FSA performs poorly on the single-peak function (Sphere), PSOEM-FSA significantly exceeds FSA, PSO-FSA and PSO on Quadric and Ackley functions. Furthermore, we can see from Table III that PSOEM-FSA promotes the performance on the most cases, especially in terms of the Best on Sphere, Rosenbrock and Quadric functions.

It can be observed from Figure 2 and Table III that PSOEM-FSA exhibits faster convergence speed and higher searching precision than other algorithms on all cases. This can be explained that PSOEM-FSA could make use of the historical information

Table II. Parameters of the algorithms

Algorithm	Parameter	Value
PSO	ω	(0.9, 0.4)
	c_1, c_2	2
PSOEM-FSA	ξ_t	0.5
	ξ_{t-1}	0.5
PSO-FSA	*Visual*	(*MaxD*, *0.01MaxD*)
	Step	(*MaxD*/5, 0)
FSA	*Try_number*	5
	δ	0.75

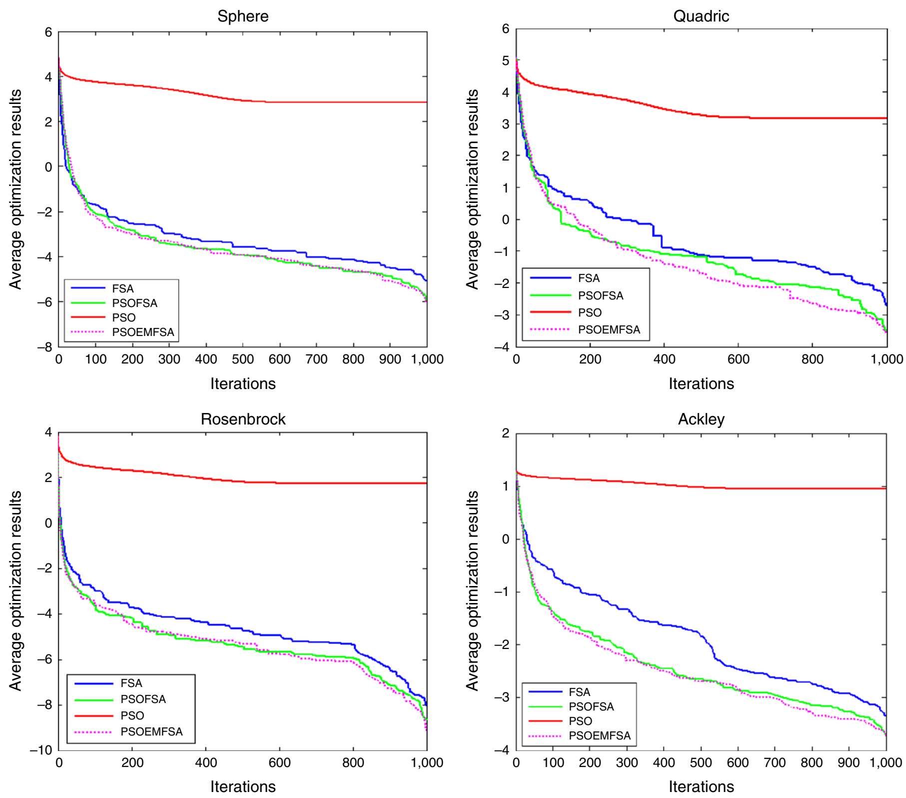

Figure 2. Convergence curves of four algorithms on four benchmark functions

Function	Program	Algorithm PSO	FSA	PSO-FSA	PSOEM-FSA
Sphere	Best	3.751e − 01	2.350e − 09	3.753e − 11	*3.082e − 13*
	Average	2.185e + 02	2.384e − 06	2.499e − 07	*6.185e − 08*
	Log10(average)	2.339	−5.623	−6.602	*−7.207*
Rosenbrock	Best	3.334e + 01	2.091e − 11	4.024e − 13	*1.988e − 14*
	Average	1.383e + 02	6.877e − 09	6.682e − 09	*6.55e − 010*
	Log10(average)	2.141	−8.16	−8.17	*−9.18*
Quadric	Best	3.545e + 02	3.883e − 07	3.484e − 07	*1.163e − 08*
	Average	3.498e + 03	1.412e − 02	3.110e − 04	*1.159e − 04*
	Log10(average)	3.544	−1.850	−3.507	*−3.936*
Ackley	Best	5.367e + 00	1.786e − 05	2.845e − 07	*1.684e − 07*
	Average	2.285	8.720e − 03	1.231e − 4	*1.018e − 4*
	Log10(average)	0.359	−2.059	−3.910	*−3.992*

Table III. Result comparison of four algorithms on four benchmark functions

stored by the extended memory to optimize the fish behavior and control the fish to search for the promising food sources.

4.1.3 Volatility analysis of optimal results. To measure the merits of the algorithm performance, one of the criteria is to find out the optimal value with desired precision. After four algorithms independently operate 50 times, we obtain the standard deviations of 50 optimization results of four algorithms. Moreover, the standard deviations are used to reflect and compare the performance of four algorithms, and they are shown in Table IV and Figure 3.

From Table IV and Figure 3, it can be seen that the standard deviations of PSOEM-FSA is the smallest among the algorithms on the four test functions, indicating that the fluctuation of the optimization results of PSOEM-FSA is the smallest, and this algorithm can guarantee higher accuracy.

4.1.4 Algorithm complexity analysis. The algorithm complexity is another standard to measure the merits of algorithm. Here, we compare the time complexity between PSOEM-FSA and the other algorithms. The convergence precision of the Quadric function is set to 1e−2, and the convergence precisions of other three functions are set to 1e−3. In addition, the other parameters of four algorithms are shown in Table II. Four algorithms independently operate 50 times, and the iteration number and optimization time which these algorithms demand to achieve the predetermined convergence precision are shown in Table V.

From Table V, it is clear that the iteration number and optimization time that PSOEM-FSA requires is obviously less than the requirements of FSA and PSO-FSA. Specially, compared to FSA and PSO-FSA, PSOEM-FSA obviously performs the superiority on Rosenbrock and Quadric functions. So, the result comparison of time

Function	Algorithm PSO	FSA	PSO-FSA	PSOEM-FSA
Sphere	1.525e + 03	8.726e − 06	1.166e − 06	1.113e − 07
Rosenbrock	3.919e − 01	2.784e − 08	1.991e − 09	1.866e − 010
Quadric	6.538e + 03	2.604e − 03	5.236e − 04	2.625e − 05
Ackley	5.799e + 00	3.492e − 04	2.681e − 04	1.106e − 04

Table IV. Standard deviations of optimization results of four algorithms

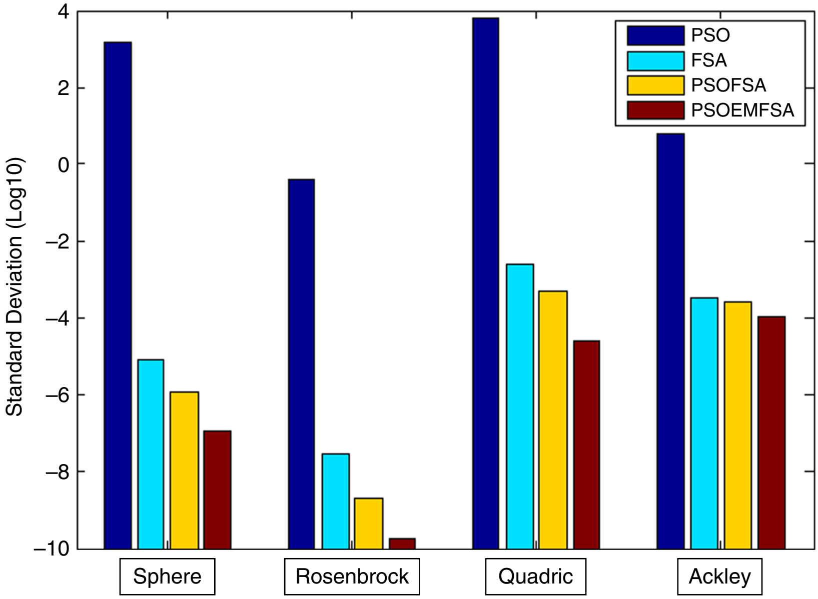

Figure 3.
Standard deviations of optimization results of four algorithms

Table V.
Result comparison of time complexity of FSA, PSO-FSA and PSOEM-FSA on three benchmark functions

	FSA		PSO-FSA		PSOEM-FSA	
Function	Iterations	Time(s)	Iterations	Time(s)	Iterations	Time(s)
Sphere	339.216	16.114	237.241	11.012	201.674	9.565
Rosenbrock	100.131	6.830	51.395	5.339	38.781	3.744
Quadric	894.788	63.347	664.685	52.672	601.330	35.213
Ackley	927.005	66.526	727.561	60.449	590.852	52.785

complexity of FSA, PSO-FSA and PSOEM-FSA tested on the three functions again verify the effectiveness of PSOEM-FSA.

4.1.5 Simulation analysis of fish behavior patterns. In order to further study the search process of the fish and verify the superiority of the proposed algorithm, simulation experiments of fish behavior patterns are performed. Specifically, the number of updating bulletin board time under each of behavior patterns is recorded, with aim of describing the contributions of four combination behavior patterns, including swarm or foraging behavior (S&F), tailgating or foraging behavior (T&F), memory or foraging behavior (M&F) and communication or foraging behavior (C&F). Especially, whether the newly introduced two combination behavior patterns (M&F and C&F) with extended memory can regularly update the bulletin board records will be observed. Based on the above observations, we can verify the significance of introducing the extended memory factor to behavior patterns of PSO-FSA (Duan *et al.*, 2013). Figures 4 and 5 indicate that four benchmark functions are optimized by PSOEM-FSA according to the parameters of Table II, and then the results of the combination of behavior model updating bulletin board are presented. The graph's horizontal axis shows iterations, and vertical axis shows the average update times.

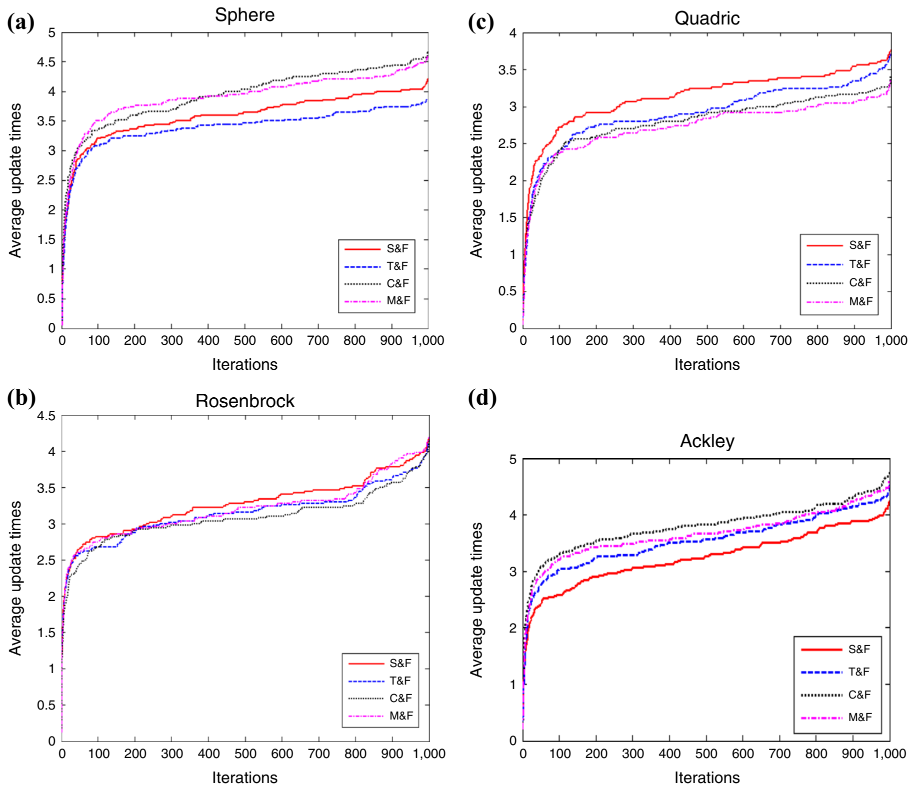

Figure 4. Bulletin board update curve of PSO-FSA

The simulation results of PSO-FSA and PSOEM-FSA are showed in Figures 4 and 5. From the results, it's clearly seen that the average update times of four combination behavior patterns updating bulletin board are slightly different, and different test functions reflect different features. Overall, four combination behavior patterns perform similarly on Ackley function, but four combination behavior patterns very differently perform on the others. What's more, by comparing Figures 4 with 5, it's obvious that the average update times of four combination behavior patterns updating bulletin board of the four benchmark functions optimized by PSOEM-FSA are obviously superior to these of PSO-FSA. From Figure 5, we can find that the two newly introduced combination behavior patterns (M&F and C&F) with extended memory can regularly update the bulletin board records, and the number of their average update time is greater than the others.

Based on the above analysis, it is verified that the introduction of new fish behaviors with extended memory makes contribution to improve the ability of algorithm optimization. Furthermore, PSOEM-FSA has better performance in convergence speed and searching precision than PSO-FSA, owning to the addition of extended memory.

5. Conclusions

In this paper, we proposed a novel optimized FSA, PSOEM-FSA. To demonstrate its effective improvement, numerical simulation experiments were performed to compare PSOEM-FSA with some exiting methods under the same parameter settings, including

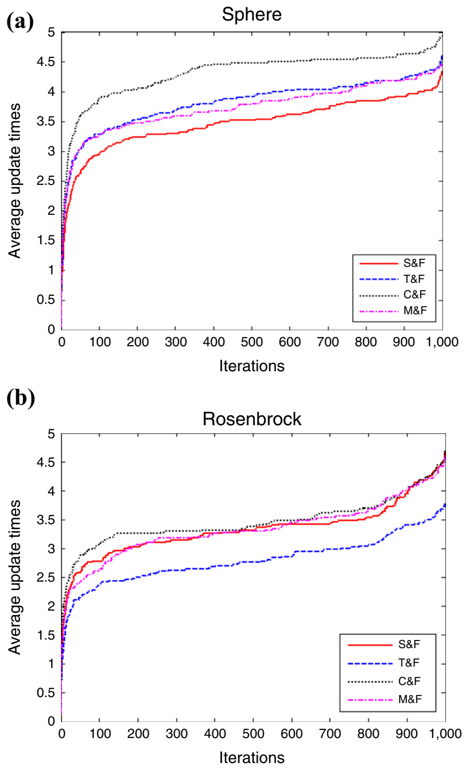

Figure 5.
Bulletin board update curve of PSOEM-FSA

PSO, FSA and PSO-FSA. Finally, experimental results show that PSOEM-FSA with appropriate parameter performs competitively in terms of commonly used performance metrics, such as convergence speed and searching precision when compared with the other algorithms in most cases. In near future study, we will conduct more experiments to make the behavior of PSOEM-FSA more understanding. In addition, the performance of PSOEM-FSA could be further improved in the following two aspects. One is the extended memory factor (ξ_{t-1}), and the other is the artificial fish of PSOEM-FSA, ensuring that the method can adjust their own visual and step length.

It is desirable to further apply PSOEM-FSA to solve those more complex real-world continuous optimization problems, such as clustering, design, data mining and optimization of communication networks. The future work also includes the studies on how to extend PSOEM-FSA to handle the combinatorial optimization problems, such as traveling salesman problem, QoS-aware service selection problem, real power line loss allocation problem and maximum power point tracking problem.

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