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Rate-Learning Based Fish School Search Algorithm for Global Optimization

Thafsouth AguerCIF, Lyes Tighzert, Boubekeur Mendil, and Cyril Fonlupt

Abstract— In this paper, we propose a new variant of fish school search algorithm, called rate-learning based fish school search algorithm (RL-FSSA), that uses a new refinement strategy to guide the population of fishes towards the best solutions. The fish motion is based on a collective sensorimotor behavior. Their learning ability determines the fish with the best position (i.e., leader). In each cycle, the best fish ever found is refined by a rate learning based process. This refinement allows a local search and decreases the effect of the hazard through time, and the whole algorithm goes from diversification towards intensification. In order to evaluate its performance, the proposed algorithm is tested under a set of benchmark functions. The numerical tests include unimodal and multimodal functions. The results show the high performance of RL-FSSA compared to the standard version FSSA. Furthermore, the computational time of the fish school search algorithm is reduced. For the validation, the algorithm is used for the trajectory planning and control of the mobile robot in an environment containing obstacles.

I. INTRODUCTION

Evolutionary algorithms are stochastic search and optimization algorithms [1]. Their origin can be traced back to the middle of the twentieth century [2-4]. They are inspired from the theory of evolution [5]. In the last two decades, researchers have proposed other algorithms inspired from the social and biological behaviors of species. In the literature we talk about swarm based intelligence [6-8]. The swarm bio-inspired algorithms tend to imitate a given social behavior of some insects, weed, and birds. This includes particle swarm optimization (PSO), ant colony (AC), bat colony (BC), invasive weed optimization (IWO) and fish school behavior.

The fish school behavior has inspired the works of Carmelo J. A. Bastos Filho who had proposed the fish school search algorithm (FSSA) [9,10]. It is known that this global search and optimization method has a good ability of global convergence, associated with its simplicity and easy implementation [10]. As a self-organizing system, it hasn't sensitivity to the initial guess of the solution.

To sum up the FSSA strategy, we summarize it through 5 steps.

1. Initialization of the population, the weight of the fish, the individual movement, the collective instinctive movement, and the collective volitive movement.

2. Individual movement: Each fish updates randomly his position. They add to each position a random number multiplied by a predetermined step called the step individual. It allows each fish to reach a neighborhood position. This is formulated as

$$N_i = x_i + rn(-1,1) \times S_{ind} \quad (1)$$

Where N_i is neighborhood position. x_i is a current position.

rn : randn(-1,1) is a normal rand vector of dimension D, D is the dimension of the problem at hand.

S_{ind} : is an individual step.

The movement only occurs if the new position N_i has a better fitness than the current position x_i . Fitness difference (Δf) and displacement (Δx) are evaluated according to:

$$\Delta f_i = f(N_i) - f(x_i) \quad (2)$$

$$\Delta x_i = N_i - x_i \quad (3)$$

3. Feeding operation: The fishes are attracted towards the food. The weights of population are updated as

$$w_i(t+1) = w_i(t) + \frac{\Delta f_i}{\max \Delta f} \quad (4)$$

4. Collective instinctive movement: The school of the fish is directed towards the same direction denoted $m(t)$, with

$$m(t) = \frac{\sum_{i=1}^N \Delta x_i \times \Delta f_i}{\sum_{i=1}^N \Delta f_i} \quad (5)$$

All fishes update their positions as follows

$$x_i(t+1) = x_i(t) + m(t) \quad (6)$$

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5. Collective volitive movement: This movement is to determine the final position of all fish school.

S_V : The step-vol parameter defines a contraction or a dilation of the swarm towards or outwards the barycenter of the school

$$b(t) = \sum_{i=1}^N x_i \times \frac{w_i(t)}{\sum w_i} \quad (7)$$

$$x(t+1) = x(t) \pm S_V \times rn(0,1) \frac{(x(t) - b(t))}{Dis(x(t), b(t))} \quad (8)$$

Researchers have developed several variants for FSSA. Some have proposed hybridization of the FSSA and the PSO [11] with application for solving non-linear equations. Others have proposed an enhancement based on genetic operator [12]. The binary representation has been proposed by A. G. João et al in [13] and the chaos artificial fish swarm [14], to cite just a few.

The performance of FSSA are discussed and analyzed in several works. It is well know that it is a very competitive one compared to other bio-inspired, swarm and population-based search algorithms. The FSSA has been applied in several domain including combinatorial optimization [15] and image processing for the multi-threshold image segmentation [16].

In this paper, we propose a refinement process to guide the fish school towards better positions (solutions). The proposed approach adds a local search algorithm to the FSSA to enhance its performance. It can be viewed as a mimetic fish school search algorithm. To well present our work, the remaining of this paper is organized as follows. The second section discusses and analysis the proposed algorithm. In order to evaluate the proposed algorithm, numerical experiments are performed and presented in the third section. The fourth section gives a real world validation in the field of mobile robots, where the proposed algorithm is used for optimal path planning while avoiding obstacles. The section five concludes this paper.

II. RATE LEARNING BASED FISH SCHOOL ALGORITHM

In this section, we introduce a new variant of FSSA. The proposed algorithm is called rate learning-based fish school search algorithm (RL-FSSA). The main idea behind RL-FSSA is to use a refinement strategy to guide the population towards best regions in the search domain. As the refinement imitates the local search algorithm, the RL-FSSA can be classified under the umbrella ground of mimetic algorithms.

The sensorimotor capability of fishes allows them to interact with their environment and between them. Each fish can move individually (autonomy) and depending on the entire swarm (collective movement). In this study, we associate for the fishes the ability of learning. This learning stage determines the moving of the best fish. It is designed as refinement procedure based on a rate-learning capacity.

The rate learning based refinement allows to RL-FSSA more diversification at the beginning and intensification over time. Like FSSA, the proposed algorithm use the same steps as well as individual movements, feeding phase, collective instinctive movement, and collective volitive movement. However, the RL-FSSA uses an extra refinement phase. In each cycle, the algorithm seeks for the position assigned to the best fish ever found and refines it by a rate learning process. Here, the proposed ‘‘rate learning’’ operation is inspired from incremental learning [17] defined by a rate-memorizing size. The main difference between our approach and incremental learning model resides in the fact that the rate learning strategy of our approach is a self-adaptive parameter that decreases through iterations. During the refinement cycles, the best fish is oriented to a new position which is computed using the memorized current position and a randomized number.

$$x_{best}^{t+1} = (1 - RL) \times x_{best}^t \pm RL \times rn(-1,1) \quad (9)$$

Where: x_{best}^{t+1} is the new position assigned to the best fish, x_{best}^t is the actual position of the best fish, RL in [0,1] is the rate learning value, and rn is a normal randomized number between [-1,1].

During the refinement cycle, the rate learning value, RL, is dumped (scaled) by a dumping parameter, chosen between 0.95 and 0.999, denoted by RL_{dump} in the pseudo of RL-FSSA shown in Fig.1

$$RL = RL \times RL_{dump} \quad (10)$$

The Fig.1 shows in more details the pseudo code of the proposed algorithm. In the initialization step, we initialize all the input parameters, the size of school fish, the maximum number of iterations, and the initial rate learning RL. The fish weighs are initialized to be one for the entire population (line 9 of the pseudo code). The main loop contains the individual movement, feeding step, the swimming collective movement and volitive movement. The latter can be attracted/repulsed towards/outwards the barycenter depending on the rate of success in the school’s last movement. In order to enhance the performance of FSSA, a refinement phase is added. In each cycle, the refinement process is executed ten times. In the first iterations, the RL-FSSA refines the best fish towards new position without taking much care on the current position. As the rate learning is decreased (dumped), the effect of the hazard will decrease through iterations, and the algorithm goes from diversification towards intensification. The parameters of this algorithm, like step individual size and step volitive size are also self-adaptive, as it is shown by lines 13 and 14 of the pseudo-code of Fig.1. In the next section, we discuss the performance of RL-FSSA.

III. BENCHMARKING OF THE RL-FSSA

In order to evaluate our algorithm, we take from the literature a set of numerical benchmark functions. This set includes unimodal and multimodal functions. The benchmark mathematical formulas, their interval and optimum positions are shown in TABLE I. The two first benchmarks are unimodal and the others are multimodal functions. The dimension D of those functions is fixed to be 30.

We compare the proposed algorithm to the standard FSSA using the benchmark cited above. Each test repeated 15 times. The parameter setting of the numerical experiments are described as follow:

- nPop: number of fish in the school : 30
- The number of fitness evaluation is set to 300 000

Algorithm1: Rate Learning based Fish School Search Algorithm

1. /* initialization */
 2. it=0 /* generation index */
 3. *MaxIt* = maximum number of generation
 4. nPop : fish school size
 5. RL= initial rate learning, RL_D= rate learning dump value
 6. Step_ind
 7. Initialization the initial step size of individual and collective movement
 8. Initialize of the population of school fish (nPop) : $x_i = \text{uniformrand}(\text{max}, \text{min})$
 9. Initialization of fish.Weigh $w_i = 1$ for all fishes
 10. Fish fitness evaluation $f_i = \text{fitness}(x_i)$
 11. **while** termination condition **do**
 12. /* Individual movement */
 13. $S_{ind} = S_{ind-int} + (S_{ind-inf} - S_{ind-int}) \times it / \text{MaxIt}$
 14. $S_v = S_{vol-int} + (S_{vol-fin} - S_{vol-int}) \times it / \text{MaxIt}$
 15. **for** i=1:N **do**
 16. $n_i = x_i + rn(-1,1) \times S_{ind}$
 17. **end for**
 18. /* feeding phase */
 19. **for** i=1:N **do**
 20. $w_i(t+1) = w_i(t) + \frac{\Delta f_i}{\max \Delta f}$
 21. **end for**
 22. /* collective instinctive movement */
 23. **for** i=1:N **do**
 24.
$$m(t) = \frac{\sum_{i=1}^N \Delta x_i * \Delta f_i}{\sum_{i=1}^N \Delta f_i}$$
 25. $x_i(t+1) = x_i(t) + m(t)$
 26. **end for**
 27. /* The collective-volitive movement */
 28. **for** i=1:N **do**
 29.
$$b(t) = \frac{\sum_{i=1}^N x_i * w_i(t)}{\sum w_i}$$
 30. $x(t+1) = x(t) \pm S_v \times rn(0,1) \frac{(x(t)-b(t))}{\text{Dis}(x(t),b(t))}$
 31. **end for**
 32. Best= seek for the best fish position ever found
 33. /* refinement the best fish position */
 34. **while** j <=10
 35. $\text{NewBest} = (1-RL) * \text{Best} + RL * \text{randn}$
 36. **if** $\text{fitness}(\text{NewBest}) > \text{fitness}(\text{Best})$ **do**
 37. $\text{Best} = \text{NewBest}$
 38. **end if**
 39. $RL = RL \times RL_{dump}$
 40. Return the best solution;
-

Fig.1 . Pseudo code of Rate Learning Fish School Search Algorithm.

TABLE I. BENCHMARK TEST FUNCTIONS AND FUNCTION PARAMETERS

Name	Equation	Search space	Optimum
Sphere function	$f_1(x) = \sum_{i=1}^D x_i^2$	$x \in [-100, 100]$	$[0 \ 0 \ \dots \ 0]^D$ D=30
Rosenbrock function	$f_5(x) = \sum_{i=1}^{D-1} 100(x_{i+1} - x_i^2)^2 + (x_i - 1)^2$	$x \in [-30, 30]$	$[11 \ \dots \ 1]^D$ D=30
Rastrigin's function	$f_6(x) = \sum_{i=1}^{D-1} [x_i^2 - 10 \cos(2\pi x_i) + 10]$	$x \in [-5.12, 5.12]$	$[0 \ 0 \ \dots \ 0]^D$ D=30
Griewank's function	$f_7(x) = \frac{1}{4000} \sum_{i=1}^D x_i^2 + \prod_{i=1}^D \cos(\frac{x_i}{\sqrt{i}}) + 1$	$x \in [-600, 600]$	$[0 \ 0 \ \dots \ 0]^D$ D=30
Ackley function	$f_9(x) = -20 \exp(-0.2 \sqrt{\frac{1}{D} \sum_{i=1}^D x_i^2}) - \exp(\frac{1}{D} \cos(2\pi x_i)) + 2 + e$	$x \in [-32, 32]$	$[0 \ 0 \ \dots \ 0]^D$ D=30

- Initial individual step = 1
- Final individual step = 0.1
- Initial weight is set to be 1.

Those common parameters are for both RL-FSSA and FSSA and they are taken from the original FSSA paper [10]. The additional RL-FSSA refinement procedure parameters are set as follows:

- Initial rate learning = 0.5
- Rate learning dump = 0.99
- The number of refinement per generation is 10.

The results of the numerical experiments are given in TABLE II. It gives the averaged value of the fitness found, for each function, for 25 independent runs. It gives also the processing time and the standard deviation. The best results are given in bold style. From the averaged values, we can study the quality of convergence. The standard deviation gives the repartition of the results around the averaged values. It is the most indicator of stability. The time processing gives the rapidity of the compared algorithm. From Table II, one can see that the proposed algorithm surpasses the original FSSA algorithm in terms of convergence quality, stability and rapidity. In the next section, we give an application of the proposed algorithm in mobile robot domain.

TABLE II. RESULTS OF THE EXPERIMENTS: MEANS, TIME PROCESSING, AND STANDARD DEVIATION OF RL-FSSA AND FSSA

Functions		F1	F2	F3	F4	F5
RLFSSA	MEAN	0.0013	14.4554	9.7261	7.2946	5.8421
	TIME	5.5913	6.4131	6.3567	6.6422	6.7465
	STD.DEV	5.9907E-4	14.4542	13.5654	12.4800	11.5343
FSSA	MEAN	0.2940	47.8327	61.1636	45.8782	36.8707
	TIME	5.7001	6.5556	6.5207	6.8154	6.9250
	STD.DEV	0.0310	65.7377	57.1026	56.0933	53.3076

IV. OPTIMAL PATH LEARNING AND OBSTACLE AVOIDANCE

A. Problem and Objective Definition:

Let us consider a mobile robot in an environment containing multiple obstacles. The objective is how to find an optimal path to reach the goal position while avoiding obstacles. This is handled in this work, using the RL-FSSA. The aim is to find a sequence of intermediary points between the initial and the goal positions. The trajectory is computed based on *spline* functions. The algorithm, iteration after iteration, will tune just the positions of the intermediary points. Each obstacle is augmented in order

to consider the robot as a point (See Fig2). Two different environment are considered here.

B. Results and discussions

Fig.2 gives the obtained results for each environment. The obtained optimal trajectory for each case is given on the left of the figure while the evolution of the optimization process is shown on the right of the figure. We note that cost function is the length of the trajectory. Although the environment contains multiple obstacles, the RL-FSSA has provided an optimal solution to avoid them.

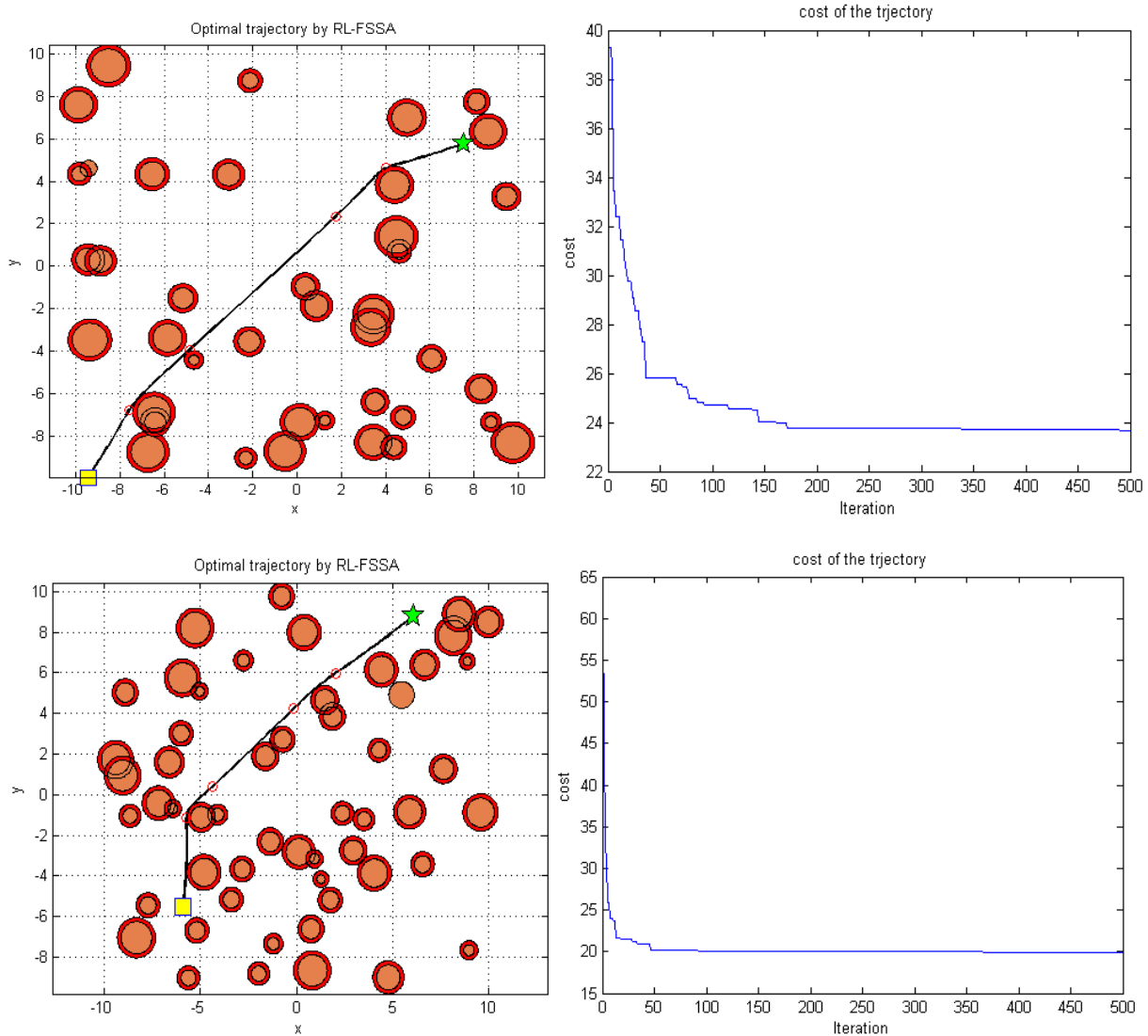


Fig.2. Results of the experiments, In the left : Optimal trajectory obtained by RL-FSSA, in the right the corresponding cost of the trajectory (optimization process)

V. CONCLUSION

In this paper, an improved version of the FSSA is introduced. The algorithm is called the rate learning based fish school search algorithm (RL-FSSA). This new variant makes use of a refinement strategy to enhance the performance of FSSA. The refinement strategy is based on a self-adaptive rate-learning parameter (RL). The fishes will learn to move to new positions while taking increasingly the influence of the current position. Therefore, the memory guidance increases through iterations. Hence, the algorithm goes from diversification towards intensification.

The proposed algorithm is tested under a set of benchmark functions. Our study is focalized on the convergence quality, the accuracy, the stability and the speediness of the proposed algorithm. The results show the high performance of RL-FSSA compared to the FSSA original version. For the validation, the proposed algorithm is used for the optimal path planning of mobile robot with obstacle avoidance. Although the environment contains multiple obstacles, the RL-FSSA provided optimal solutions to avoid them.

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