Elite-Leading Fireworks Algorithm

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Abstract. Fireworks algorithm (FWA) is effective to solve optimization problems as a swarm intelligence algorithm. In this paper, the elite-leading fireworks algorithm (ELFWA) is proposed based on dynamic search in fireworks algorithm (dynFWA), which is an important improvement of FWA. In dynFWA firework is separated to two group: core-firework (CF) and non-core fireworks (non-CFs). This paper takes some beneficial information from non-CFs to reinforce the local search effect of CF. Random reinitialization and elite-leading operator are used to maintain the diversity of the non-CFs, which play an important role in global search. Based on the CEC2015 benchmark functions suite, ELFWA has a very competitive performance when comparing with state-of-the-art fireworks algorithms, such as dynFWA, dynFWACM and eddynFWA.

Keywords: Fireworks algorithm · Elite-leading operator · Random reinitialization

1 Introduction

Both in the academic field and in the industrial world, many problems can be simplified as optimization problems. In order to solve those problems many swarm intelligence (SI) algorithms were proposed in recent years. Fireworks algorithm (FWA) [1], proposed by Tan and Zhu in 2010, is one of SI algorithms based on simulating the fireworks explosion process. The performance of twelve evolutionary algorithms are tested and compared by Bureerat in 2011 [2], in which FWA ranks at the sixth, which verifies that FWA works effectively on some optimization problems.

Due to its bloom developing, FWA has many improved variants to enrich its research field. The Enhanced Fireworks Algorithm (EFWA) [3], proposed by Zheng et al. in 2013, is an important improvement of the FWA. Five main operators of the FWA have been improved or corrected in the EFWA, which are the methods of calculating explosion amplitude, generating new explosion sparks, generating Gaussian sparks, selecting the population for the next iteration and the new mapping strategy for sparks which are out of the search space. Hence, some algorithms, like dynFWA, are

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applied to the EFWA rather than FWA. Based on the EFWA, Zheng et al. [4] proposed Dynamic Search in Fireworks Algorithm (dynFWA) in 2014. In dynFWA, fireworks are separated into two groups. The first group consists of the firework with best fitness named core firework (CF), while the second group consists of all other fireworks named non-core fireworks (non-CFs). Compared with non-CFs, the explosion amplitude of CF is smaller, hence CF is good at local search. Non-CFs have larger explosion amplitudes which are fitter for global search. Moreover, the biggest difference between two groups is that the CF has very high probability to generate the best candidate which will be selected to the next iteration as firework.

Based on the dynFWA Yu et al. [5] proposed the dynamic fireworks algorithm with covariance mutation (dynFWACM) in 2015. It introduced the mutation operator into dynFWA, which calculates the mean value and covariance matrix of the better sparks and produces sparks according to Gaussian distribution. Zheng et al. [6] proposed an exponentially decreased dimension number strategy based dynamic search fireworks algorithm (eddynFWA) in 2015. Yu et al. [7] put forward a new FWA with differential mutation (FWA-DM) by using differential operator in 2014. Li et al. [8] proposed an adaptive fireworks algorithm (AFWA) in 2014. Zhang et al. [9] proposed an improving enhanced fireworks algorithm (IEFWA) with new Gaussian explosion and population selection strategies.

Moreover, many developments for multi-objective optimization have also been proposed. Zheng et al. [10] proposed a multi-objective fireworks optimization for variable-rate fertilization in oil crop production. Tan [11] proposed an S-metric based multi-objective fireworks algorithm in 2015. FWA has also been applied to many practical fields and problems. FWA has been used for digital filters design [12], pattern recognition [13] and so on.

2 dynFWA

In dynFWA [4] firework is separated into two groups. One group is named as Core Firework (CF) and the other is non-core fireworks (non-CFs). In each iteration, CF means the firework with the currently best fitness and non-CFs mean all the rest fireworks. The main operations of dynFWA are listed as follows.

2.1 Calculate the Numbers of Explosion Sparks

In order to take full advantage of all the fireworks, different fireworks have different numbers of sparks in dynFWA, which depends its fitness as Eq. (1).

$$S_i = M_e \cdot \frac{\mathrm{y}_{\max} - f(X_i) + \varepsilon}{\sum_{\mathrm{j}=1}^{N} (y_{\max} - f(X_j)) + \varepsilon} \tag{1}$$

In this equation, S_i represents the number of sparks for the firework i, M_e controls the number of sparks. $\mathrm{y}_{\max} = max(f(X_i))$, $f(X_i)$ denotes the fitness value of the firework i. N is the number of fireworks.

2.2 Calculate the Explosion Amplitude

Fireworks with better fitness should have smaller explosion amplitudes to bias the local search. On the contrary, fireworks with worse fitness should have larger explosion amplitudes to bias the global search. So dynFWA uses Eq. (2) to calculate the explosion amplitude for non-CF.

$$A_i = \hat{A} \cdot \frac{f(X_i) - y_{\min} + \varepsilon}{\sum_{j=1}^{N} (f(X_j) - y_{\min}) + \varepsilon} \tag{2}$$

In this equation, A_i represents the explosion amplitude of the firework i, $\hat{A}$ controls the explosion amplitude of sparks. $y_{\min} = \min(f(X_i)), f(X_i)$ denotes the fitness value of the firework i. N is the number of fireworks.

But for CF, the explosion amplitude is generated with Eq. (3). Parameters C_a and C_r are used to control the amplification and reduction ratio of the exploitation amplitudes.

$$A_{CF}(t) = \begin{cases} C_{\mathrm{a}} \times A_{CF}(\mathrm{t}-1) & \text{if } \mathrm{f}(\mathrm{X}_{CF}(\mathrm{t})) < \mathrm{f}(\mathrm{X}_{CF}(\mathrm{t}-1)), \\ C_r \times A_{CF}(\mathrm{t}-1) & \textit{otherwise}. \end{cases} \tag{3}$$

2.3 Generate the Explosion Sparks

After getting the information of explosion sparks and explosion amplitude, each firework explodes and creates explosion sparks with Eq. (4).

$$X_i^k = \begin{cases} X_i^k + A_i \times rand(-1,1) & \text{if firework is non-CF} \\ X_{CF}^k + A_{CF} \times rand(-1,1) & \text{if firework is CF} \end{cases} \tag{4}$$

X_i^k is the i-th firework and A_i is the explosion amplitude, rand (−1,1) represents a random number between −1 and 1.

The location of a new spark will be mapped within the search space with Eq. (5) if it exceeds the search range in dimension k.

$$X_i^k = X_{\min}^k + rand * (X_{\max}^k - X_{\min}^k) \tag{5}$$

3 Elite-Leading Fireworks Algorithm (ELFWA)

Before proposing the Elite-leading Fireworks Algorithm (ELFWA), the difference between CF and non-CFs in the dynFWA should be introduced. The biggest difference is that CF has more chance to generate a better spark and then be selected into the next iteration. The main role of non-CFs is to keep population diversity and perform global search. But the global search is possible to be more effective if other more effective operations were used and the CF's effect is possible to be more obvious if more sparks were given. Based on this motivation, a new improvement of dynFWA, Elite-leading Fireworks Algorithm (ELFWA) is proposed. When comparing to dynFWA, the CF in ELFWA have more sparks and the non-CFs will generate none sparks. As a compensation, non-CFs will run another operation to evolve constantly for global search.

3.1 CF Operations

Some operations of CF in ELFWA will be introduced. (1) In ELFWA, CF denotes the global best solution which is the optimal solution found until now. (2) Different from dynFWA, the number of sparks in ELFWA is not alterable. In this paper the number of CF sparks is a constant which is equal to the number of non-CFs. (3) The method of calculating explosion amplitude of CF is not changed and Eq. (3) is also used. (4) The way of CF generating sparks is the same as dynFWA doing in Eq. (4). (5) CF will be updated with the best solution from non-CFs or sparks of CF at the current iteration or the global best solution in the previous iteration, depending on the fitness as Eq. (6) illustrates.

$$CF(t) = \arg\min\{f(nonCF(t)), f(SparksOfCF(t)), f(CF(t-1))\} \tag{6}$$

3.2 Non-CFs Operations

A new strategy is proposed and utilized to the non-CFs which includes two operations, i.e., random reset operation and Elite-leading operation. Random reset operation decides whether to reset the non-CFs with a probability. If a random number r_1 is less than the given probability, non-CFs will be reinitialized with Eq. (7).

$$nonCF_i^k = X_{\min}^k + rand * (X_{\max}^k - X_{\min}^k) \tag{7}$$

$nonCF_i^k$ represents the k-th dimension of the i-th non-CF.$X_{\max}^k$ and $X_{\min}^k$ represent the upper bound and lower bound of the k-th dimension.

After non-CFs are reinitialized, all solutions will be redistributed in the search space again and usually become worse. So in order to scan more a little more beneficial areas ELFWA uses Elite-leading operation to improve the quality of non-CFs at the successive iteration with Eq. (8).

$$nonCF_i(t) = nonCF_i(t-1) + rand(0,1) * (\mathrm{gBS}(t{-}1) - \mathrm{lBS}(t{-}1)) \tag{8}$$

In Eq. (8), gBS(t-1) indicates the global best solution and lBS(t-1) indicates the best solution in the non-CFs of the previous iteration. It will be changed when the non-CFs are reinitialized. rand(0,1) is a random number between 0 and 1. It will be found that all the non-CFs have the same directions, which is decided by gBS and lBS. This process can be regarded as the best solution of the current non-CFs leading all the non-CFs to the best one of them. Additionally, gBS is equal to the CF, so gBS is very crucial for the algorithm. That is why this research is named as Elite-leading Fireworks Algorithm.

The mapping operator of the ELFWA is changed into Eq (9).

$$X_i^k = \begin{cases} \min(X_{\max}^k, 2 * X_{\max}^k - X_i^k)) & if\, X_i^k > X_{\max}^k \\ \max(X_{\min}^k, 2 * X_{\min}^k - X_i^k)) & if\, X_i^k < X_{\min}^k \end{cases} \tag{9}$$

After mapping operation, ELFWA evaluates the quality of the explosion sparks and non-CFs. So, the framework of Elite-leading Fireworks Algorithm (ELFWA) is presented as follows.

```
Initialize N/2 fireworks as non-CFs
Evaluate non-CFs and set non-CFs' best as CF
while termination criteria are not met do
     %%CF operation:
     Calculate explosion amplitude for CF (Eq.(2));
     Generate explosion sparks (Eq.(4));
     Map sparks to search space (Eq.(9));
     %%Non-CF operation:
     If r1 < 0.05
        Reinitialize the non-CFs, evaluate the quality of
        non-CFs and reset lBS;
     End if
     Update non-CFs (Eq.(7));
     Map non-CFs back to search space (Eq.(9));
     Evaluate quality of explosion sparks, non-CFs;
     if f(nonCFs(t-1))< f(nonCFs(t))
        update explosion amplitude of non-CFs;
     Update explosion amplitude of CF (Eq.(3));
End while
Output the final solution(s) and the fitness.
```

4 Experiment and Analysis

15 benchmark functions of CEC 2015 [14] competition are used to verify the effectiveness of ELFWA. Following four state-of-the-art algorithms are compare toELFWA, EFWA [3], dynFWA [4], dynFWACM [5] and eddynFWA [6].

4.1 Experimental Setup

Several parameters in ELFWA are set as follows. The dimension of benchmark function is 30. Parameters C_a and C_r in Eq. (3) are empirically set to 0.9 and 1.1. In order to make full use of the ability of global search of CF, A_{CF} is set to the size of the space in the beginning. Both the number of non-CFs and the number of sparks are 50 in ELFWA. All the algorithms are performed 30 runs on each benchmark functions; the final mean results are recorded with 300 000 function evaluations.

4.2 Experimental Results and Analysis

The online performance comparison of five FWA algorithms is shown as Fig. 1, which clearly shows that ELFWA is effective. Especially, ELFWA is very effective for f1, f2, f6, f8, f10 and f12. For functions f3 and f5, all algorithms nearly find the same results. For the rest functions, although ELFWA does not perform best, it can find a competitive solution in short time with the less benchmark functions evaluations.

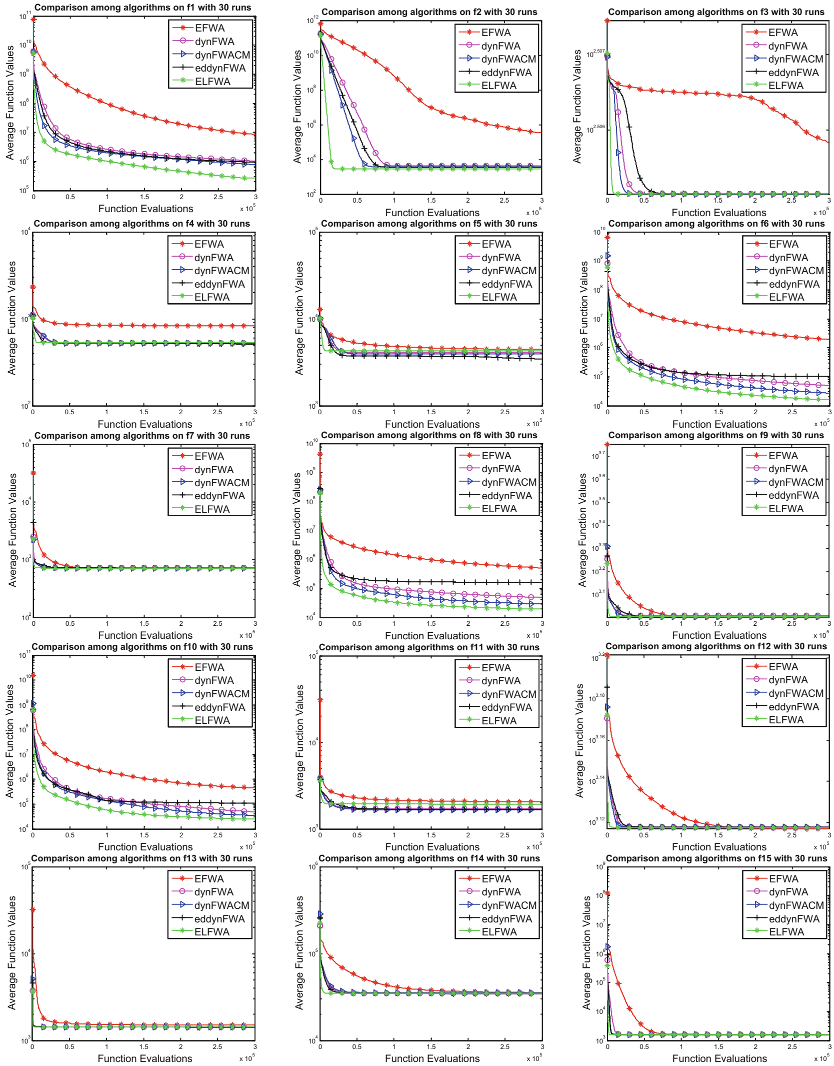

Fig. 1. Online performance comparison among algorithms

Table 1 shows that three improvements of dynFWA are better than dynFWA and all of four dynFWAs outperform EFWA. Among them, ELFWA is the slightly best one both in mean value and in the best solution, a little better than, or performs comparably with dynFWACM and eddynFWA. According to the general ranks of several FWA variants, eddynFWA, dynFWACM and ELFWA have similar ranks, however, ELFWA has the best rank. When comparing with dynFWA, ELFWA outperforms dynFWA on 10 from 15 benchmarks and performs equally on 2 functions. dynFWA slightly outperforms, however, comparably with ELFWA on other 3 functions. The value of std. also shows that the result of ELFWA is relatively stable and robust. In order to compare the difference between the existing algorithms and ELFWA, the value of student test is given. If the mean value of ELFWA is smaller than the mean value of existing algorithms and the Wilcoxon's rank-sum test under 5% significance level is true, then it is believed that the results of ELFWA are significant better than existing algorithms. In Table 1, an algorithm which is significant better than ELFWA is marked with '+', no performance significant difference is marked with '≈', significant worse than ELFWA is marked with '−'. In Table 1, ELFWA is significant better than those four algorithms at 13, 10, 8, 7 functions. The performance of ELFWA at other functions is competition with those four algorithms.

Table 1. The result of the experiment

	dynFWA			dynFWACM			eddynFWA			ELFWA	
	Mean	Std		Mean	Std		Mean	Std		Mean	Std
f1	1.03E+06	3.23E+05	–	7.71E+05	4.53E+05	–	9.52E+05	6.34E+05	–	**2.67E+05**	**1.37E+05**
f2	4.24E+03	3.93E+03	–	3.78E+03	4.02E+03	–	3.54E+03	4.06E+03	–	**2.92E+03**	**3.15E+03**
f3	3.20E+02	5.87E−06	≈	3.20E+02	1.51E−05	≈	3.20E+02	1.88E−06	≈	**3.20E+02**	**2.64E−03**
f4	5.26E+02	3.35E+01	≈	5.23E+02	3.51E+01	≈	**3.20E+02**	3.34E+01	≈	5.30E+02	**3.32E+01**
f5	4.10E+03	7.01E+02	≈	3.95E+03	6.85E+02	≈	**3.46E+03**	**6.60E+02**	≈	4.28E+03	8.64E+02
f6	4.96E+04	3.62E+04	–	2.72E+04	2.07E+04	–	1.01E+05	6.12E+04	–	**1.63E+04**	**1.02E+04**
f7	7.18E+02	1.37E+01	–	7.15E+02	**4.73E+00**	≈	**7.17E+02**	1.51E+01	≈	7.18E+02	1.27E+01
f8	4.85E+04	1.95E+04	–	2.87E+04	1.34E+04	–	**1.59E+05**	**1.03E+05**	–	1.92E+04	1.10E+04
f9	1.02E+03	6.15E+01	–	1.01E+03	3.58E+01	≈	**1.01E+03**	3.34E+01	≈	1.01E+03	**3.97E+01**
f10	4.91E+04	1.66E+04	–	3.45E+04	1.36E+04	–	1.10E+05	**6.88E+04**	–	**2.48E+04**	1.22E+04
f11	1.71E+03	2.60E+02	≈	**1.66E+03**	2.44E+02	≈	1.68E+03	**2.10E+02**	≈	1.93E+03	2.15E+02
f12	1.31E+03	1.94E+00	–	1.31E+03	1.98E+00	–	1.31E+03	1.95E+00	–	**1.31E+03**	**1.71E+00**
f13	1.43E+03	**5.79E+00**	–	1.43E+03	6.91E+00	–	**1.41E+03**	7.68E+00	≈	1.43E+03	7.44E+00
f14	3.50E+04	1.75E+03	–	3.55E+04	1.86E+03	–	**3.47E+04**	1.43E+03	≈	3.49E+04	**1.42E+03**
f15	1.60E+03	8.76E−12	–	1.60E+03	8.52E−13	≈	1.60E+03	4.53E−13	–	**1.60E+03**	**9.23E−13**
Rank	3.13			2.26			2.2			2.13	

5 Conclusion and Future Work

An improved variant of dynFWA is proposed based on the information borrowing and elite leading strategies in this paper. In order to explore whether strengthen the search ability of elites is effective. Based on the two groups of dynFWA, this paper uses some beneficial information of non-CFs to reinforce the effect of CF. Another strategy is used to maintain the diversity of the non-CFs and to make them play an important role in global research. The experiments show that this inspiring motivation works well. The proposed ELFWA algorithm significantly outperforms dynFWA and performs a little better than, and comparably with two recently enhanced dynFWAs, i.e., dynFWACM and eddynFWA. In the future, more useful global research operators will be considered to improve FWA algorithm and other SI algorithms.

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