Collaborative Diversity Control Strategy for Random Drift Particle Swarm Optimization*

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ABSTRACT

Random drift particle swarm optimization (RDPSO) is a swarm intelligence algorithm inspired by the trajectory analysis of the canonical particle swarm optimization (PSO) and the free electron model in metal conductors placed in an external electric field. However, the RDPSO algorithm may easily encounter premature convergence when solving multimodal optimization problems. In order to deal with this issue, a new collaborative diversity control strategy for RDPSO is presented in this paper. Within this strategy, two kinds of diversity measures are used and changed in a collaborative manner to make the evolving process of the RDPSO controllable, so that premature convergence can be avoided and a final good solution can be found. Experimental results, when comparing with the canonical RDPSO and the canonical RDPSO using ring neighborhood topology, show that the proposed collaborative diversity control strategy can significantly improve the performance of the RDPSO algorithm for multimodal optimization problems in most cases.

CCS CONCEPTS

Computing methodologies → Artificial intelligence → Search methodologies → Heuristic function construction

KEYWORDS

Collaborative diversity control strategy, random drift particle swarm optimization algorithm, multimodal optimization problems

1 INTRODUCTION

The random drift particle swarm optimization (RDPSO) algorithm was proposed based on the basic theory of particle swarm optimization (PSO) [1], along with the trajectory analysis of its canonical version [2] and the analogy with the free electron model in metal conductors placed in an external electric field [3]. The algorithm is illustrated in detail in [4]. However, some limitation of the RDPSO algorithm is its ability to escape from local optima in the search process, especially in multimodal optimization problems. To deal with this issue, a novel strategy called collaborative diversity control (CDC) strategy for RDPSO is introduced in this paper. Using the CEC-2013 benchmark, the RDPSO algorithm with CDC strategy is compared with the canonical RDPSO (α is decreasing linearly from 0.9 to 0.3 with $\beta = 1.45$), and canonical RDPSO using ring neighborhood topology, to verify the effectiveness of the proposed strategy.

2 COLLABORATIVE DIVERSITY CONTROL

In order to quantify the distribution of the particle swarm, the definition of swarm diversity [5] is used in this paper:

$$D(X_n) = \frac{1}{M\cdot A}\sum_{i=1}^{M}[\sum_{j=1}^{N}[X_{i,n}^{j} - \overline{X_n^j}]^2]^{1/2} = \frac{1}{M\cdot A}\sum_{i=1}^{M}\left|X_{i,n} - \overline{X_n}\right| \quad (1)$$

where A is the diagonal length of the search space, M is the number of individuals in the swarm, and N is the dimensions of each individual. $X_{i,n} = (X_{i,n}^1, X_{i,n}^2, \cdots, X_{i,n}^N)$ is the current position vector

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of particle i at the n^{th} iteration, and the mean value of all individuals' j^{th} dimension is $\overline{X_n^j}$.

In this paper, the diversity values of two populations are used: $D(X_n)$ and $D(P_n)$, which are the diversity values of all particles' current positions and personal best positions, respectively. Basically, the global and local search ability of the RDPSO algorithm is related to the relationship between these two swarm diversities. Based on this, the Collaborative Diversity Control strategy for RDPSO is proposed. By comparing $D(X_n)$ and $D(P_n)$ in each iteration, several sub-strategies are observed, which are listed below:

A. The baseline for $D(P_n)$. Firstly, a decreasing baseline of $D(P_n)$ is set, using a polynomial form in terms of the iteration number, which is expressed as:

$$B_i = (1 - n/n_{max})^c * (B_{n,start} - B_{n,end}) + B_{n,end} \tag{2}$$

$$B_{n,end} = eratio * B_{n,start} \tag{3}$$

where n represents the n^{th} iteration of the algorithm and n_{max} is the maximum number of iterations. c is a constant which determines the decline rate of the baseline. $eratio$ determines the particles' final searching area. $B_{n,start}$ is set to $D(P_1)$, and $B_{n,end}$ is set to a certain ratio multiplied by $B_{n,start}$. Empirically, $c = 7$ and $eratio = 1 \times 10^{-4}$ are set, which can give the CDC strategy a good performance on multimodal optimization problems.

B. Divergence of particles. When $D(X_n)$ and $D(P_n)$ are both lower than the current value of the baseline, the particles' search area should be too small to search globally. Therefore, in this sub-strategy, the value of α increases with the decline of $D(X_n)$ according to equation (4), while $\beta = 1.45$ is kept constant, to make the particles diverge, enlarging the search area.

$$\alpha = \alpha_0 / Dr(X_n), Dr(X_n) = D(X_n)/D(X_1) \tag{4}$$

where $Dr(X_n)$ shows how small the particles' diversity is. α_0 is set to 0.9, making particles diverge moderately at the beginning.

C. Global search of particles. When $D(X_n)$ is higher than the baseline, along with $D(P_n)$ still lower than the baseline, we set $\alpha = 0.9$ and $\beta = 1.45$ to let the algorithm search globally, considering the relatively large distance between $D(X_n)$ and $D(P_n)$.

D. Accelerated convergence of particles. Finally, if $D(P_n)$ is larger than the value of the baseline, α and β is set to decrease linearly from 0.9 to 0.3 and 1.45 to 1.05 in term of the iteration number, respectively, to accelerate the convergence process, making the particles search more locally as necessary.

3 RESULTS AND DISCUSSION

The multimodal functions F_6 to F_{20} from the CEC-2013 benchmark suite [6] are employed to evaluate the effectiveness of the RDPSO-CDC algorithm, compared with the canonical RDPSO and canonical RDPSO using ring neighborhood topology (RDPSO-Ring), as the ring neighborhood topology is basically designed for multimodal optimization problems [7]. The dimension of each tested benchmark function is 30, and the max iterations is set to 3×10^4, using 100 particles. Each function is optimized 51 times. The size of the ring neighborhood topology is set to 3. Table 1 records the average final fitness values and the best final fitness values for each algorithm.

In Table 1, the better results among RDPSO-CDC and RDPSO are bold. For the mean values and the best values, RDPSO-CDC gets better results in almost every function only except the mean value in F_{10} and the best value in F_6. Secondly, the result with an underline in each function is the better one among RDPSO-CDC and RDPSO-Ring. Only in F_6, F_{12}, F_{13}, F_{15} for the mean values, and F_6 for the best values, RDPSO-Ring is the winner, while in all the other functions RDPSO-CDC is the better one. Thus, it can be concluded that for the RDPSO algorithm, CDC strategy can significantly improve the performance of dealing with multimodal problems, and its effectiveness is better than RDPSO-Ring.

Table 1: Mean and Best Values for Three Algorithms

	RDPSO	RDPSO -CDC	RDPSO -Ring	RDPSO	RDPSO -CDC	RDPSO -Ring
	Mean Value			Best Value		
F_6	3.59E+01	**2.56E+01**	7.86E+00	**1.05E+01**	1.46E+01	1.79E-01
F_7	3.81E+00	**2.96E+00**	5.53E+00	3.86E-01	**1.96E-01**	1.66E+00
F_8	2.09E+01	**2.08E+01**	2.09E+01	2.07E+01	**2.07E+01**	2.07E+01
F_9	1.10E+01	**1.08E+01**	1.24E+01	4.84E+00	**4.17E+00**	7.87E+00
F_{10}	**3.03E-02**	4.47E-02	4.66E-02	8.10E-03	**7.40E-03**	9.86E-03
F_{11}	1.01E+01	**1.02E+00**	1.11E+01	3.98E+00	**2.76E-10**	5.97E+00
F_{12}	4.58E+01	**3.08E+01**	2.87E+01	1.31E+01	**1.20E+01**	1.99E+01
F_{13}	8.19E+01	**6.31E+01**	6.08E+01	3.43E+01	**1.50E+01**	3.62E+01
F_{14}	8.87E+02	**3.84E+02**	7.42E+02	2.71E+02	**2.52E+01**	2.80E+02
F_{15}	6.12E+03	**4.24E+03**	3.98E+03	3.04E+03	**1.71E+03**	1.96E+03
F_{16}	1.99E+00	**1.97E+00**	2.02E+00	1.40E+00	**1.05E+00**	1.20E+00
F_{17}	4.78E+01	**3.50E+01**	5.60E+01	3.58E+01	**3.06E+01**	4.77E+01
F_{18}	1.76E+02	**1.35E+02**	1.54E+02	1.52E+02	**5.91E+01**	1.05E+02
F_{19}	2.63E+00	**1.50E+00**	2.16E+00	1.57E+00	**1.01E+00**	1.58E+00
F_{20}	1.34E+01	**9.68E+00**	1.02E+01	8.12E+00	**7.75E+00**	9.24E+00

4 CONCLUSIONS

In this paper, we proposed a collaborative diversity control strategy for the RDPSO algorithm, in order to avoid local optima when using RDPSO for multimodal optimization problems. By comparing the RDPSO-CDC algorithm with canonical RDPSO and the ring neighborhood topology, the experimental results significantly indicate the effectiveness of the CDC strategy.

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