A Population Entropy Based Adaptation Strategy for Differential Evolution

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ABSTRACT

We introduce a new enhanced algorithm with a population entropy based population adaptation strategy under the framework of SHADE (PE-SHADE). The distribution state of the population is characterized, and then the population size is adapted with a population increasing strategy and a population reduction strategy. Experimental results on CEC2014 statistically support the effectiveness of the proposed algorithm.

CCS CONCEPTS

• **Mathematics of computing → Evolutionary algorithms**; **Continuous optimization**; • **Theory of computation** → *Evolutionary algorithms*;

KEYWORDS

Differential Evolution, Population Adaptation, Population Entropy

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1 INTRODUCTION

Due to its simple structure, easy implementation and fewer control parameters, Differential Evolution (DE) [5] has attracted substantial attention in both theoretical studies and engineering applications. Among the three basic control parameters of DE, the population size (PS) has a influence on the allocation and balance of resources. An Excessive PS is good for global exploration but consumes many fitness evaluations. Otherwise, a too small PS will make for exploitation but easily leads to early convergence as well. Although the research on PS is not so mature, many achievements have also been made [4].

The entropy is one of the parameters that characterize the state of matter in thermodynamics, and is used as a measure of the degree of chaos in the system. In this paper, a population-entropy-based method is proposed to characterize the distribution state of the population along with a population increasing strategy and a reduction strategy. And then a new algorithm PE-SHADE is proposed as an enhancement of the algorithm SHADE [6].

2 PE-SHADE

In this paper, all of the entropy values mentioned below are calculated based on the expression of the information entropy. In order to simplify the calculation, the entropy value of dimension i at generation g is calculated first as Eq. 1 shows.

$$E_{i,g} = -\sum_{j=1}^{PS} p_{j,g} \log p_{j,g} (i = 1, ..., D) \tag{1}$$

where each dimension in the decision space is evenly divided into PS intervals, D denotes the problem dimension, and at generation g, the probability that the individuals fall into each interval is $p_{j,g}$.

$$p_{j,g} = \frac{N_{j,g}}{PS} (j = 0, ..., PS) \tag{2}$$

where $N_{j,g}$ is the number of individuals fall into the j-th interval of dimension i at generation g. Then the entropy value of each dimension is multiplied as the final population entropy value E_g at generation g.

$$E_g = \prod E_{i,g} (i = 1, ..., D) \tag{3}$$

Each generation, the ratio of the current population entropy value and the one at last generation is calculated to judge the population distribution state, according to which the corresponding PS adaptation strategy is adopted. The ratio R can be expressed as following.

$$R = \frac{E_{g+1}}{E_g} \tag{4}$$

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Every N generations, namely $mod(g, N) = 0$ where g refers to the current generation, the average value of the R values is calculated, denoted by R_{avg}, and then determine how to adapt the PS value. The setting of $N = 4$ is referred to [4]. When the number of evaluations $NEFs < 0.2 \times MaxNEFs$, it is believed that if $rand(0, 1) > R_{avg}$, R_{avg} is probably a small value, so the population become concentrated at the early stage. At this time, $rate_1 \times PS$ individuals are randomly generated to help slow down the converging. If the PS exceeds the upper bound PS_{max}, it will be truncated to PS_{max}. And when $NEFs \geq 0.2 \times MaxNEFs$, the convergence speed is considered slow if $rand < R_{avg}$, and the worst $rate_2 \times PS$ individuals will be removed from the population. The population size can be reduced to the lower bound PS_{min} at most. Here, $rate_1 = 0.3$, $rate2 = 0.05$, and it will be discussed in detail in Section 3.

3 EXPERIMENT

This section discusses the performance of the proposed PE-SHADE on the *CEC2014 Special Session on Real-Parameter Single Objective Optimization* benchmark suit [3], including the performance comparisons with SHADE[6], L-SHADE[7], UMOEAs[2], CoDE[8], JADE[9] and jDE[1]. Experiments were conducted on CEC2014 benchmark ($D = 30, 50, 100$) and $MaxNFEs = 10000 \times D$. For each function, each algorithm was tested on it for 51 times, and the performances of the algorithms were evaluated in terms of function error value [3], defined as $f(X) - f(X^*)$, where X^* was the global optimum of the test problem. When the function error was less than 10^{-8}, it was treated as 0, and the average of the 51 function error values for each function was evaluated. The PS varies in a given range, and $PS_{max} = 10 \times D$, $PS_{min} = D$, while the initial population size $PS_{init} = 100$, which have referred to some conclusions in [4].

Table 1: Comparisons between PE-SHADE and DE variants on CEC2014 benchmark D=30, 50, 100

D		SHADE	UMOEAs	CoDE	JADE	jDE	L-SHADE
D=30	+	2	4	2	2	2	12
	-	18	18	19	22	22	5
	=	10	8	9	6	6	13
D=50	+	5	4	3	4	2	10
	-	16	21	24	21	23	10
	=	9	5	3	5	5	10
D=100	+	4	10	3	2	4	11
	-	16	15	22	23	19	11
	=	10	5	5	5	7	8

The results are shown in Table 1. To effectively analyze the results, the Wilcoxon's rank-sum test at $\alpha = 0.05$ was performed to help compare the performance. In the tables, the symbols $'+', '-', '='$ respectively mean that the corresponding algorithm is significantly better than, significantly worse than or comparable with the proposed algorithm PE-SHADE on CEC2014 benchmark problems.

In general, the comprehensive improvements of PE-SHADE, compared with SHADE, over these three dimensional problems, have clearly proven the effectiveness of the proposed PS adaptation strategy, while the comparisons with UMOEAs and the classic DE variants, namely CoDE, JADE and jDE, show the advantages of PE-SHADE as a whole. When comparing with L-SHADE, PE-SHADE is worse than L-SHADE on the 30-dimensional problems, however, it performs comparably to L-SHADE on the 50-dimensional problems and 100-dimensional problems. This indicates that PE-SHADE also has potential for competing with other PS adaptation algorithms.

The parameters $rate_1$ and $rate_2$ were used to control the increasing rate and reduction rate of the population size respectively. A simple sensitive test has been done about these two parameters, where $rate_1 = 0.1, 0.3, 0.5$ and $rate_2 = 0.05, 0.1, 0.3$, and the experiments have been done with the random combinations of these values of these two parameters on CEC2014 benchmarks with $D = 30, 50, 100$. Due to the space constraints, the detailed results will not be shown here. Overall, the combination $rate_1 = 0.3, rate_2 = 0.05$ is recommended.

4 CONCLUSIONS

This paper has proposed an extension variants of SHADE, namely PE-SHADE, with a population entropy-based PS adaptation strategy, and the experimental results have shown the effectiveness and efficiency of PE-SHADE. Nevertheless, some more attention should be paid to the deeper impact of PS adaptation strategy on the changing of population distribution states and the division of the search space when calculating the population entropy.

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