Postprint: Optimal Parameter Study of the Shuffled Frog Leaping Algorithm

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Abstract

This section describes the optimal parameter selection process for the Shuffled Frog Leaping Algorithm (SFLA). Given fixed population size and total number of iterations, the number of memeplexes, the maximum step size allowed for position changes of individual frogs, and the number of iterations within each memeplex are critical parameters that influence the optimization performance of the SFLA. Different parameter value selections produce varying effects on the algorithm' s outcomes. To determine appropriate values for these three parameters, we first conducted an analysis of their impacts on the algorithm. Subsequently, three commonly used values were selected for each parameter, and a three-factor, three-level experiment was designed using orthogonal experimental design methodology. Under identical environmental conditions, the CEC2013 real-parameter function test suite was employed to validate the optimization performance of the algorithm across different parameter combinations. Finally, using the Friedman test score on optimal value errors as the evaluation metric, the optimal parameter combination (20, 5, 10) was identified, establishing a foundation for subsequent algorithm improvement and application.

Full Text

Preamble

Research on Optimal Parameters of Shuffled Frog Leaping Algorithm

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Abstract: This paper investigates the optimal parameter selection process for the shuffled frog leaping algorithm (SFLA). Given fixed population size and total iteration count, three critical parameters significantly affect SFLA' s optimization performance: the number of groups, the maximum step size allowing individual frog position changes, and the number of intra-group iterations. Different parameter values yield varying algorithmic outcomes. This study first analyzes parameter impacts on the algorithm, then selects three commonly used values for each parameter to design a three-factor, three-level experiment using orthogonal experimental design. Under identical environmental conditions, the CEC2013 real-parameter function test suite validates the optimization performance of different parameter combinations. Finally, using the Friedman test score of optimal value error as the evaluation metric, the optimal parameter combination (20, 5, 10) is identified, providing a foundation for subsequent algorithm improvements and applications.

Keywords: shuffled frog leaping algorithm; orthogonal experiment; CEC2013 evaluation standard; parameter selection

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0 Introduction

Swarm intelligence optimization algorithms typically contain multiple freely configurable parameters, and different parameter selections significantly impact convergence capability and optimization performance. Therefore, researching parameter values in algorithms holds substantial value. When comparing algorithm performance, a reasonable and comprehensive evaluation standard is needed to assess solution accuracy, efficiency, and effectiveness. Reference [1] proposed a dynamic parameter ant colony algorithm built upon a QoS (Quality of Service) evaluation model that derives a fitness function F (where smaller F indicates better results), achieving faster convergence efficiency by varying parameters across different stages. Reference [2] introduced an adaptive genetic algorithm approach for SVM parameter selection, automatically adjusting crossover and mutation probabilities based on fitness values to reduce convergence time and improve accuracy, thereby ensuring reliable SVM parameter selection.

The shuffled frog leaping algorithm (SFLA) [3] is a novel heuristic population evolution algorithm proposed by Eusuff and Lansey in 2003. It combines the strengths of two swarm intelligence optimization algorithms: the memetic algorithm (MA) [4] based on meme evolution and the particle swarm optimization (PSO) [5] based on population behavior. With multiple adjustable parameters, SFLA presents significant research value and practical importance. Numerous scholars have studied SFLA and applied it across various research domains, yet no comprehensive evaluation standard for its parameter selection has been established. Parameter research is crucial both for improving SFLA' s inherent performance and for its application to other research areas. Consequently, this paper conducts systematic experiments and analyses on optimal parameter selection for SFLA, addressing test problem selection and design, experimental methodology determination, and statistical analysis of results using SPSS software to ultimately identify the optimal parameter combination.

1.2 Parameter Impact Analysis on the Algorithm

As introduced above, with frog population size N and total iterations G fixed, the primary parameters affecting SFLA performance are: group count p (since total frogs N is fixed, frogs per group $m = N/p$ is not considered separately), maximum step size $D_{\max}$ allowing individual frog position changes, and intra-group iteration count L. We theoretically analyze each parameter' s impact on algorithmic performance.

First, consider group count p. If p is too small, information exchange within subpopulations becomes insufficient, hindering effective local search. If p is too large, excessive mixing frequency between subpopulations reduces comprehensive information exchange, causing the algorithm to converge prematurely to local optima.

Second, maximum step size $D_{\max}$ controls the algorithm' s global search capability. If $D_{\max}$ is too small, global search weakens, trapping the algorithm in local optima. If $D_{\max}$ is too large, the algorithm may skip the true global optimum.

Finally, intra-group iteration count L behaves similarly to $D_{\max}$. If L is too small, frogs within subpopulations jump too frequently, preventing comprehensive information exchange. If L is too large, subpopulations may converge to local optima.

2.1 Test Problems

In recent years, numerous swarm intelligence optimization algorithms—including ant colony algorithms [6], particle swarm optimization, cuckoo search [7], and bat algorithms [8]—have been widely applied to real-parameter function optimization problems in engineering design and scientific domains [9-11], significantly improving problem-solving efficiency. However, these studies often employ different test function sets (e.g., Ackley, Griewank, Rastrigin, Rosenbrock, Quadric, Shubert functions) without a unified, comprehensive evaluation standard, representing a serious limitation. Using partial test functions impedes thorough algorithm research and analysis, while inconsistent environmental settings across studies hinder result comparisons and subsequent work.

To address this, Suganthan et al. proposed standardized test function suites encompassing unimodal, multimodal, and composite functions for comprehensive algorithm performance testing and analysis. As this paper focuses on single-objective real-parameter function optimization, we adopt the CEC2013 evaluation standard [12].

SFLA' s fundamental concept involves generating an initial population of N frogs and randomly initializing each individual' s position within the solution space range, represented as $S = \{X_1, X_2, ..., X_N\}$. Assuming solution space dimension D, the i-th frog is $X_i = [x_{i1}, x_{i2}, ..., x_{iD}]$. After initialization, all frogs are sorted by fitness value from best to worst, with the best frog position denoted X_g. The population is then divided into p groups, each containing m frogs ($N = p \times m$). Let M_k represent the k-th frog group; the allocation process follows equation (1).

After grouping, the best and worst fitness positions in each group are denoted X_b and X_w, respectively. Local search proceeds in each group via the worst frog update formula in equation (2).

$$D = \text{rand}() \cdot (X_b - X_w), \quad X'_w = X_w + D, \quad |D| \leq D_{\max}$$

where rand() generates a random number in $[0, 1]$ and $D_{\max}$ is the maximum allowed step size. After one iteration, if $f(X'_w) < f(X_w)$, the position is retained and the group' s worst frog updates; otherwise, X_g replaces X_b in equation (2). If neither operation improves the frog' s position, a random individual replaces X_w. This local search repeats L times, after which all frogs are reshuffled via equation (1) and the process continues until convergence or maximum iterations $G_{\max}$ is reached.

2.2 CEC2013 Evaluation Standard

The CEC2013 real-parameter test function suite, proposed by Suganthan et al. in 2013, improves upon the CEC2005 composite functions with new test functions for greater comprehensiveness. The suite contains 28 test functions: 5 unimodal functions, 15 basic multimodal functions, and 8 composition functions. This diverse set enables thorough algorithm performance testing and analysis. Detailed function descriptions appear in Table 1 .

2.3 Experimental Environment Settings and Evaluation Metrics

As analyzed above, inconsistent environmental settings affect algorithm performance and hinder comparisons. Therefore, we standardize all experimental conditions: population size $N = 300$, dimension $D = 20$, independent runs = 100, search range $[-100, 100]$ (encompassing all function optima), and algorithm termination upon reaching maximum iterations or when the minimum fitness value falls below 10^{-6} (set to 0 if below 10^{-6}). The evaluation metric is mean error—the difference between the minimum fitness value and theoretical optimum. Specific settings are shown in Table 2 .

3 Parameter Selection for Shuffled Frog Leaping Algorithm

Orthogonal arrays are complete, rule-based design tables that reduce trial counts and improve testing efficiency. For a three-factor, three-level experiment, comprehensive testing requires $3^3 = 27$ combinations, yet orthogonal tables can reflect the full experiment with only 9 trials.

Orthogonal experimental design [13] has demonstrated outstanding design capabilities across medicine, chemical engineering, biology, electronics, military, and other fields. It effectively addresses parameter determination for intelligent optimization algorithms through multi-parameter, multi-level experiments.

3.1 Introduction to Orthogonal Experimental Design

Orthogonal experimental design selects "uniformly dispersed, comparably neat" points from comprehensive trials based on orthogonality, identifying optimal factor-level combinations. With advantages of efficiency, speed, and economy, it has become widely adopted. This method studies multi-factor, multi-level designs by selecting representative points for testing and identifying optimal combinations.

3.2 Selecting SFLA Optimal Parameters via Orthogonal Design

Section 1.2 analyzed parameter impacts, revealing that maximum step size $D_{\max}$ primarily affects global search capability, while group count p and intra-group iteration count L mainly influence local search capability. All three parameters degrade convergence performance if too large or too small, necessitating appropriate intermediate values. Proper $D_{\max}$ enhances global search, exploring more potential solutions for better convergence. Appropriate p and L strengthen local search, reducing local optima entrapment.

This section employs orthogonal design for SFLA parameter selection using CEC2013 test functions as the evaluation standard:

a) Define experimental purpose and evaluation metrics. The goal is identifying optimal SFLA parameter combinations for CEC2013 test functions. The evaluation metric is the Friedman test ranking score of optimal value errors across 28 test functions, where lower scores indicate superior parameter combinations.

b) Select influence factors and determine factor levels. The primary parameters are group count p, maximum step size $D_{\max}$, and intra-group iteration count L. These three parameters serve as orthogonal design factors, each divided into three common levels based on typical SFLA settings, as shown in Table 3 .

c) Select orthogonal experimental design table. Traditional orthogonal table selection is cumbersome and inefficient. SPSS, a software for statistical analysis, data mining, and decision support, streamlines this process. We use SPSS 20.0 to design the orthogonal table and analyze results, significantly improving efficiency. The three-factor, three-level orthogonal table designed via SPSS appears in Table 4 .

d) Develop and execute experimental scheme. The nine experimental schemes ignore factor interactions. Based on Tables 3 and 4, we implement the orthogonal design trials shown in Table 5 . Experiments follow the parameter combinations in Table 5 with environment settings from Section 2.3 and maximum iterations $G_{\max} = 500$. The evaluation standard is the Friedman ranking score across CEC2013's 28 functions, where smaller error (the evaluation metric) yields better performance, thus lower ranking scores indicate superior combinations.

e) Experimental result analysis. With fewer trials than comprehensive testing, data processing is crucial. Intuitive analysis (range analysis) and variance analysis are common orthogonal experiment methods. Range analysis determines factor importance via range values, while variance analysis quantitatively assesses factor impacts. We first use intuitive analysis to identify factor significance and obtain a superior combination, then employ SPSS for detailed variance analysis to verify results and determine factor influence magnitudes, presented in Tables 6 through 8 .

Table 6 shows single-factor results, where R represents the range value indicating impact magnitude. The R values are: factor A $(p) = 9$, factor B $(D_{\max}) = 2.80$, factor C $(L) = 1$. Thus, p has the greatest impact, with factor importance ranking: $p > D_{\max} > L$. The preliminary optimal combination is A2B3C1.

Tables 7 and 8 present between-subjects effects tests and estimated marginal means. F values reflect factor impact magnitudes (larger F = greater impact), and Sig. values indicate significance (larger significance = greater impact). The parameter importance ranking is $p > D_{\max} > L$, consistent with Table 6' s range analysis. Since smaller Ranking values represent better performance, Table 8 reveals optimal factor levels: group count $p = 20$, maximum step size $D_{\max} = 5$, intra-group iterations $L = 10$. The final optimal parameter combination appears in Table 9 .

These results demonstrate that appropriate parameter selection enhances global and local search capabilities, enabling faster convergence to superior solutions and validating theoretical analysis. This approach also provides a methodology for parameter selection in other problem domains: identify parameters and their common values, select a comprehensive evaluation standard, then test different combinations to identify the optimal set.

4 Conclusion

Applying swarm intelligence optimization algorithms often involves parameter setting challenges, and SFLA is no exception. Superior parameter combinations enable faster convergence to better solutions. This paper first introduced the CEC2013 real-parameter test suite as an evaluation standard, then systematically examined common SFLA parameter combinations to identify the optimal set via orthogonal experimental design, establishing a foundation for algorithm improvement and broader application.

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Note: Figure translations are in progress. See original paper for figures.