A Two-Stage Coevolution Approach for Constrained Optimization

Jing-Yu Ji
Sun Yat-sen University
Guangzhou, China

Wei-Jie Yu*
Sun Yat-sen University
Guangzhou, China
Email:ywj21c@163.com

Jun Zhang
South China University of Technology
Guangzhou, China

ABSTRACT

In this paper, a coevolution approach with two stages is proposed for constrained optimization problems (COPs). At the first stage, the approach enters the feasible region rapidly by utilizing the feasibility rule with incorporation of objective function information (FROFI), which is an effective method for the balance between constraints and objective function. At the second stage, the population of the first stage coevolves with an additional population to locate the global optimum. The additional population is generated when a feasible solution is found. Penalty function as a constraint-handling technique is employed on the additional population. By means of coevolution, elite individuals from the original population and the newly generated population are exchanged to promote each other for the global optimum. The performance of our approach is evaluated on a suite of benchmark functions from IEEE CEC 2010. Experimental results have shown that the proposed approach generally outperforms four other state-of-the-art constrained optimization algorithms on most of the benchmark functions.

CCS CONCEPTS

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

KEYWORDS

Constrained optimization, coevolution, penalty function

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1 INTRODUCTION

Optimization problems involving inequality and/or equality constraints are widely found in many real-world applications from diverse domains[4]. The coevolution method utilizing multiple populations is a promising approach to deal with COPs. Different populations with different evolutionary operators coevolve to locate the optimal solution efficiently. This paper proposes a novel coevolution approach to solve COPs. There are two search stages in the optimization process of the proposed approach. The first stage aims to find feasible region rapidly, and the second stage focuses on locating optimal solution in feasible region at the end. At the first stage, FROFI [8] as one of elite constrained optimization EAs is utilized to find feasible region at a fast speed by incorporating the objective function information. However, when the search enters the feasible region, it would be trapped into local optima. Hence, at the second stage, an additional population is generated and coevolves with the original population to enhance the global search ability. The additional population employs penalty function as constraint-handling technique. Since penalty function considers the constraints and objective function information simultaneously, it is helpful to search the feasible region in diverse directions. The original population and the newly generated population share search information by exchanging elite individuals, which can help the search avoid local optima. As a result, an approach based on coevolution with two stages named CO-TS, is developed in this paper. Experiment comparisons and analyses among CO-TS and four state-of-the-art constrained optimization EAs have been conducted on a suite of benchmark functions from IEEE CEC 2010 [3]. The experimental results show that CO-TS generally outperforms the other four algorithms and have significant improvements to FROFI on several test functions.

2 FROFI

FROFI contains three main components, i.e., differential evolution (DE)[6] as the search algorithm, the replacement mechanism, and the mutation strategy, which can balance constraints and objective function for COPs. These three components relieve the greediness in entering feasible regions and improve the achievement of finding optimal solution. Moreover, the information of objective function is fully utilized in the three components during the search procedure.

3 THE PROPOSED CO-TS

CO-TS solves a COP in two stages. At the first stage, CO-TS starts as FROFI works in [8]. When one feasible solution is found, which means the search enters the feasible region, the second stage starts. An additional population is generated

*Corresponding author.

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Table 1
Wilconxon's Test Results for CO-TS, FROFI, εDEg, AIS-IRP and ECHT-ARMOR-DE

Comparison	R^+	R^-	R	p-value
CO-TS versus FROFI	330	291	45	5.09E-1
CO-TS versus εDEg	462	176	28	1.36E-2
CO-TS versus AIS-IRP	554	111	1	5.01E-4
CO-TS versus ECHT-ARMOR-DE	506	124	36	1.02E-3

and coevolves with the original population. For the newly generated population, penalty function is employed to calculate the fitness value of each individual. The individuals are compared based on their fitness values instead of feasibility rule. For a specific individual $\mathbf{x}$, its fitness value ϕ is calculated as follows:

$$\phi(\mathbf{x}) = f(\mathbf{x}) + \sum_{j=1}^{m} G_j(\mathbf{x}) \quad (1)$$

In the initialization phase, a population P with N individuals is randomly generated in decision space $\mathbf{S}$. In addition, a set A is initialized to archive individuals with small objective function values. Then, at the first stage, CO-TS utilizes the feature of FROFI to find feasible region by evolving population P. Once a feasible solution is found, the second stage starts and an additional population Q is initialized by duplicating the N individuals of P. Afterward, the two distinct populations cooperatively deal with COPs.

4 EXPERIMENTAL STUDY

In this section, experiments are carried out to evaluate the performance of the proposed CO-TS. We employ 18 benchmark constrained optimization functions with $10D$ and $30D$ from IEEE CEC 2010 [3]. These 18 benchmark functions have different characteristics, e.g., separable, nonseparable, and rotated. More details of these test functions can be found in [3].

We compare the proposed CO-TS with four state-of-the-art constrained optimization algorithms, namely, FROFI[8], εDEg [7], AIS-IRP [9] and ECHT-ARMOR-DE [2] on all the test functions. To test the statistical differences, Wilcoxon's test [5] and the Friedman's test [1] are employed on the mean objective values of 18 functions obtained by the five algorithms. The test results are summarized in Table 4 and 5. From Table 4, it can be observed that CO-TS beats the other four algorithms since it provides higher R^+ values than R^- values in all the cases. Moreover, the ranking from Table 5 indicates that CO-TS works the best among these algorithms.

5 CONCLUSION

In this paper, a two-stage coevolution approach, namely, CO-TS has been proposed to solve COPs. CO-TS deals with a COP in two stages. FROFI with its advantage has been utilized to find feasible region rapidly at the first stage. When a feasible solution is found, the second stage of CO-TS starts. An additional population is generated and penalty function is employed on it. By coevolution, the exchanged information from different population enhances the global search ability of CO-TS to avoid local optima. In addition, experimental results have demonstrated that CO-TS exhibits better or at least competitive performance against other three state-of-the-art algorithms. Future work will focus on the extension of CO-TS for large-scale COPs as well as the application of CO-TS to real-world engineering problems.

Table 2
Friedman's Test Results for CO-TS, FROFI, εDEg, AIS-IRP and ECHT-ARMOR-DE

Algorithms	ranking
CO-TS	2.4306
FROFI	2.4722
εDEg	3.1389
AIS-IRP	3.5694
ECHT-ARMOR-DE	3.3889

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