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A Single Component Mutation Evolutionary Programming

Mingjun Ji *, Hualong Yang, Yongzhi Yang, Zhihong Jin

Transportation Management College, Dalian Maritime University, Dalian 116026, People's Republic of China

A R T I C L E I N F O

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A B S T R A C T

In this paper, a novel evolutionary programming is proposed for solving the upper and lower bound optimization problems as well as the linear constrained optimization problems. There are two characteristics of the algorithm: first, only one component of the current solution is mutated in each iteration; second, it can solve the linear constrained optimization problems directly without converting it into unconstrained problems. By solving two kinds of the optimization problems, the algorithm can not only effectively find optimal or close to optimal solutions but also reduce the number of function evolutions compared with the other heuristic algorithms.

1. Introduction

Many problems in scientific and technological fields involve global optimization. In most cases they consist not only of a nonlinear objective function that has to be optimized, but of a number of linear or nonlinear constraints that must be satisfied as well. Several gradient algorithms have been developed for handling the constrained optimization problems, which is usually done by converting them into unconstrained ones [1–3]. Despite their progress in solving the global optimization problems in recent years, gradient optimization algorithms have only been able to tackle special formulations because they depend on the existence of derivatives, and they are insufficiently robust in discontinuous, vast multimodal [4]. Therefore, it is of great importance to explore other effective algorithms.

Some heuristic methods have been developed for solving the global constrained optimizations problems [5,6]. For example, a classical study on evolutionary algorithms for constrained optimization problems has been published by Michalewicz [4]. Among these methods, those based on penalty functions have been proven to be the most popular. However, penalty function methods are also characterized by serious drawbacks, since small values of the penalty coefficients drive the search outside the feasible region and often produce infeasible solution [7,8].

Evolutionary programming is one of the general metaheuristics known as evolutionary algorithm (EA) [9] which includes genetic algorithms, evolutionary strategies, genetic programming and evolutionary programming [10]. It is attractive because it does not rely on any gradient information and yet its global convergence guaranteed [11,12]. The classical evolutionary programming was proposed by Fogel [9,13]. Yao et al. [14] put forward the fast evolutionary programming in 1999. Iwamatsu [15] proposed the generalized evolutionary programming. Considering its excellent performance in solving the unconstrained optimization problems, Some researchers are now trying to apply the evolutionary programming to solve the constrained optimization problems.

In this paper, we further develop the evolutionary programming and put forward the *Single Component Mutation Evolutionary Programming* (SCMEP) for solving the upper and lower bound optimization problems as well as the linear constrained

* Corresponding author.
E-mail address: jmj012001@yahoo.com.cn (M. Ji).

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optimization problems. The characteristic of SCMEP is that only one component of the current solution is mutated in each iteration. Moreover, it can directly solve the constrained optimization problems without penalty coefficients. SCMEP is easy to manipulate and proven to be effective. SCMEP is described in Section 2. Section 3 shows two applications of SCMEP and its numerical results for solving sixteen optimization problems. The effective analysis of SCEMP is given in Section 4. Finally, Section 5 concludes with some remarks and future research directions.

2. Single Component Mutation Evolutionary Programming

Considering the following global optimization problem

$$(P)\quad \begin{cases} \min f(x), \\ s.t.\ x \in \Omega, \end{cases} \tag{2.1}$$

where $\Omega \subseteq R^n$ and f is a real-valued function defined on Ω. The Single Component Mutation Evolutionary Programming (SCMEP) for solving the problem (P) is implemented as follows:

Step 1. Generate the initial population of μ individuals, and set $k = 1$. Each individual is taken as a pair of real-valued vectors, $(x_j, \eta), \forall\, j \in \{1, \ldots, \mu\}$, where x_j's are objective variables and η is standard deviation for Gaussian mutations (also known as strategy parameters in self-adaptive evolutionary algorithms).

Step 2. Evaluate the fitness score for each individual $(x_j, \eta),\ \forall\, j \in \{1, \ldots, \mu\}$, of the population on the objective function, $f(x_j)$.

Step 3. Each parent $(x_j, \eta),\ j = 1, \ldots, \mu$, creates a single offspring (x'_j, η') by the following formulas:Randomly choose a $l_j \in \{1, 2, \ldots, n\}$, then for $i = 1, \ldots, n$

$$x'_j(i) = \begin{cases} x_j(i) + \eta N_j(0,1), & i = l_j, \\ x(i), & i \neq l_j, \end{cases} \tag{2.2}$$

$$\eta' = \eta\ exp\ (-\alpha), \tag{2.3}$$

$N_j(0,1)$ denotes a normally distributed one-dimensional random number with mean zero and standard deviation one. In this paper, $\alpha = 1.01$ and the initial value of η is equal to 1. If $\eta < 10^{-4}$, then $\eta = 1$.

Step 4. Calculate the fitness of each offspring $(x'_j, \eta'),\ \forall j \in \{1, \ldots, \mu\}$.

Step 5. Conduct pairwise comparison over the union of parents (x_j, η) and offspring $(x'_j, \eta'),\ \forall\, j \in \{1, \ldots, \mu\}$. For each individual, q opponents are chosen uniformly at random form all the parents and offspring. For each comparison, if the individual's fitness is no smaller than the opponents's, it receives a "win".

Step 6. Select the μ individuals out of (x_j, η) and $(x'_j, \eta'), \forall j \in \{1, \ldots, \mu\}$, that have the most wins to be parents of the next generation.

Step 7. Stop if the halting criterion is satisfied ; otherwise, $k = k + 1$ and go to step 3.SCMEP is a global optimization algorithm, whose characteristic is that only one component of each solution is mutated in each iteration. It can reduce the CPU time because only one component of the solution is mutated compared with the mutation of all components.

3. Computational experiments

Our new approach is used to solve two cases. One case is the optimization problems with the upper and lower bounds, the other is the optimization problems with the linear constraints. Numerical results for two cases are showed.

3.1. The upper and lower bound problems

The constrained set of the upper and lower optimization problems is described as $\Omega := \{x | x(i) \in [a(i), b(i)],\ i = 1, 2, \ldots, n\}$, where $a(i),\ b(i)$ are the lower bound and upper bound of the component $x(i)$ respectively. Based on the above description, the step 3 of SCMEP is implemented as follows:

Step 3. Each parent $(x_j, \eta),\ j = 1, \ldots, \mu$, creates a single offspring (x'_j, η') by the following formulas:

(3.1) randomly choose a $l_j \in \{1, 2, \ldots, n\}$, then for $i = 1, \ldots, n$

$$x'_j(i) = \begin{cases} x_j(i) + \eta(b(i) - a(i))N_j(0,1), & i = l_j, \\ x(i), & i \neq l_j, \end{cases} \tag{3.1}$$

$$\eta' = \eta\, exp(-\alpha), \tag{3.2}$$

(3.2) x'_j can be a feasible solution by the formula: