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A hybrid memetic algorithm for global optimization

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ABSTRACT

A hybrid memetic algorithm, called a memetic algorithm with double mutation operators (MADM), is proposed to deal with the problem of global optimization. In this paper, the algorithm combines two meta-learning systems to improve the ability of global and local exploration. The double mutation operators in our algorithms guide the local learning operator to search the global optimum; meanwhile the main aim is to use the favorable information of each individual to reinforce the exploitation with the help of two meta-learning systems. Crossover operator and elitism selection operator are incorporated into MADM to further enhance the ability of global exploration. In the first part of the experiments, six benchmark problems and six CEC2005's problems are used to test the performance of MADM. For the most problems, the experimental results demonstrate that MADM is more effective and efficient than other improved evolutionary algorithms for numerical optimization problems. In the second part of the experiments, MADM is applied to a practical problem, clustering complex and linearly non-separable datasets, with a satisfying result.

1. Introduction

In computational intelligence, more and more school learners put their attentions to the new field of memetic algorithms. Memetic algorithms [1] proposed by Pablo Moscato is based on the simulation of the process of cultural evolution. It is a marriage between a population-based global search and the heuristic local search made by each of the individuals. Some publications [2,3] introduced memetic algorithms associated with global search and local learning. The local learning mechanism is often regarded as a meme to enhance the ability of local convergence. A few of researchers make use of memetic algorithms to solve the real word problems [4–7].

Before Darwin published the Darwin's theory of natural evolution, Lamarck proposed that the characteristics of organism's life could be learned and passed on to their offspring [8]. Inspired from the Lamarckian evolutionary theory, a novel algorithm based on the theory of Lamarckian learning is designed. From the literature [9], we know that traditional immune optimization algorithms have used a single mutation operator, typically Gaussian mutation or Cauchy mutation. From the literatures [10–14], it is obvious that Cauchy mutation performs better when the current search point is far away from the global minimum, while Gaussian mutation is better at finding a local optimum in a good region. To cooperate with local search operators, two mutation operators can guide the individual to learn from the environment. After the double mutation, one meta-learning operator is applied to all the individuals and reducing the blindness of individual learning. Crossover operator and elitism selection operator are incorporated into MADM to further enhance the ability of global exploration. Crossover operator provides enough diversity for population, but it also gives some unexpected solutions. After crossover, another local learning operator is applied to the individuals and refines capabilities of search algorithms.

In this paper, a hybrid memetic algorithm with double self-adaptive mutation operators (MADM) is present. The performance of MADM is evaluated by solving some benchmark problems and CEC2005's problems. Furthermore, we applied MADM to solving the complex and linearly non-separable datasets clustering problem. The rest of the paper is organized as follows: Section 2 introduces an outline of MADM. This section also describes MADM in detail, and analyzes the action of all operators. Section 3 shows the experimental results of the algorithms: differential evolution with local neighborhood (DELG) [15], Lamarckian learning in clonal selection algorithm (LCSA) [16], covariance matrix adaptation evolution strategy (MADA and CMA-ES) [17]. We also choose six CEC2005's functions [18] to evaluate the performance of MADM. In Section 4, to evaluate the proposed method, the performance of the proposed method will be compared with KM [19], K-KM [20], GK-KM [21] and spectral clustering algorithm [22] (SC) over a test suit of several interesting data sets. Finally, we have a brief conclusion in Section 5.

2. The description of MADM

Fig. 2 shows the pseudo code of MADM and Fig. 3 shows the overall structure of MADM. Note that learning operator can guide

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the process of evolution. It enhances the genotype to influence the better results which replaced the locally improved individual back into population to compete for reproductive opportunities. After crossover performance, another local learning operator is applied to the individuals and refines the capabilities of search algorithms.

2.1. The double mutation operators design

2.1.1. Cauchy mutation operator design

With the action of global Cauchy mutation operator, the relationship of the parent $(x_i(j), \sigma_i(j))$ and their offspring $(x_i'(j), \sigma_i'(j))$ is showed as follows:

$$x_i'(j) = x_i(j) + \sigma_i'(j) C_j(0,1) \quad (i = 1, \ldots, m; j = 1, \ldots, n), \tag{1}$$

$$\sigma_i'(j) = \sigma_i(j) \exp\left(\lambda \frac{aff_{x_i} - aff_{ave}}{aff_{\max} - aff_{\min}}\right) \quad (i = 1, \ldots, m; j = 1, \ldots, n) \tag{2}$$

Where m is the scale of population, and n is the dimension of problem. $x_i(j), x_i'(j), \sigma_i(j)$ and $\sigma_i'(j)$ denoted the j-th component of the vectors x_i, x_i', σ_i and σ_i', respectively. $C_j(0,1)$ denotes Cauchy random variable with the scale parameter $t = 1$. aff_{x_i} is fitness of the current individual, $aff_{\max}$is the maximum fitness of the current population, $aff_{\min}$ is the minimum fitness of the current population. aff_{ave} is the average fitness of the current population. $\lambda = 1$ or -1(maximum problem $\lambda = -1$, minimum problem $\lambda = 1$). Based on Eq. (2), for the minimum problems, it can infer that it is needed to reduce the size of local search when $aff_{x_i} < aff_{ave}$. It means that the solution is near the optimum. Otherwise it should increase the size of local search to search the solution which is far away from optimum.

2.1.2. Gaussian mutation operator design

With the action of Gaussian mutation operator, the relationship of the parent $(x_i(j), \sigma_i(j))$ and their offspring $(x_i'(j), \sigma_i'(j))$ is as follows:

$$x_i'(j) = x_i(j) + \sigma_i'(j) N_j(0,1) \quad (i = 1, \ldots, m; j = 1, \ldots, n), \tag{3}$$

$$\sigma_i'(j) = \sigma_i(j) \exp\left(\frac{-\mu\kappa + \sqrt{\mu\kappa}}{2}\right) \quad (i = 1, \ldots, m; j = 1, \ldots, n). \tag{4}$$

Where the meaning of the variables m, n, $x_i(j), x_i'(j), \sigma_i(j)$ and $\sigma_i'(j)$ are the same as those in Eqs. (1) and (2). $N_j(0,1)$ denotes a normally distributed one-dimensional random number with mean

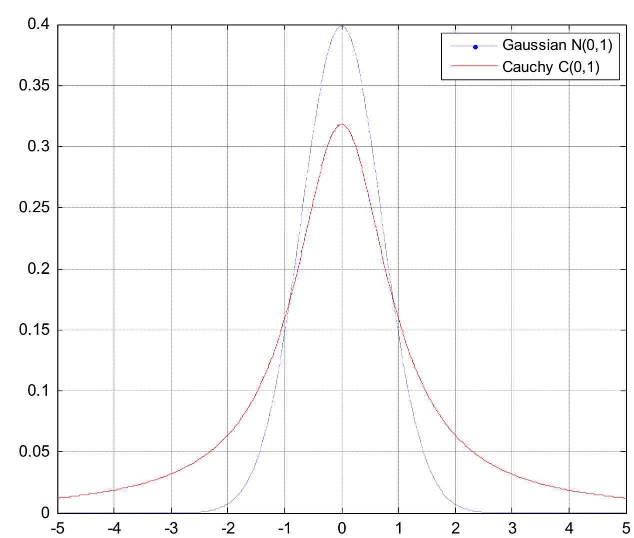

Fig.1. Cauchy and Gaussian density functions values.

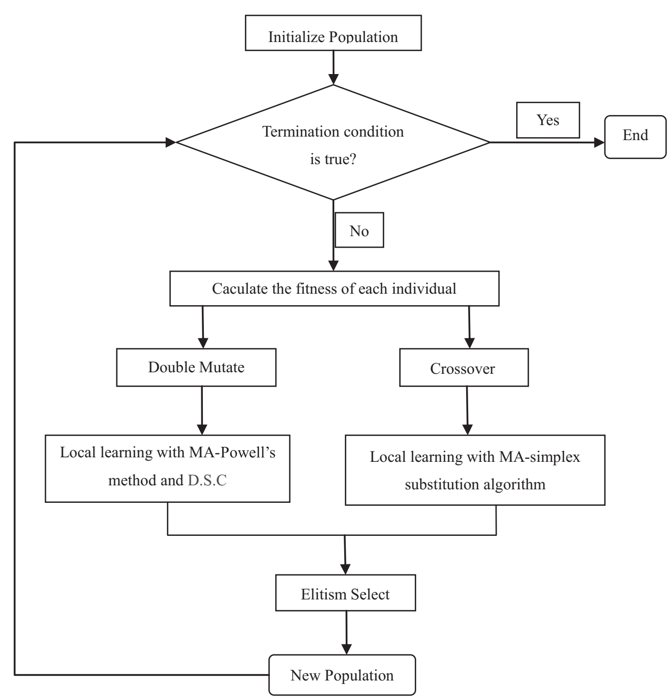

Fig. 3. Overall structure of MADM.

Step 1: (Initialization) Generate an initial population randomly;
Step 2: while the stopping conditions are not satisfied do;
Step 3: (Calculate the fitness) Evaluate the fitness of all individuals in the population;
Step 4: (Reproduction) According to the individual scale and fitness, the reproduction of the selected individuals;
Step 5: (Meta-Powell's add D.S.C local learning operator)
For each individual **do**
If it is satisfied the given condition: Cauchy mutation of the individual;
Else: Gaussian mutation of the individual;
End if
Perform Powell's add D.S.C local method of the individual and Proceed Lamarckian learning spirit;
End for
Step 6: (Crossover) Execute Crossover operator on the population;
(Meta-simplex substitution local learning operator)
Perform simplex substitution algorithm of the individual and Proceed Lamarckian learning spirit;
Step 7: (Elitism selection) Calculate the fitness of individual, and apply elitism to the selected individual;
Step 8: (Termination) **end while**.

Fig. 2. The pseudo code of MADM.