Adaptive Genetic Algorithm Based on Density Distribution of Population

Ni Chen[1], Jun Zhang[1] (Corresponding Author) and Ou Liu[2]
[1]Department of Computer Science, Sun Yat-sen University, P.R. China
[1]Key Laboratory of Digital Life, Ministry of Education, P.R. China
[1]Key Laboratory of Software Technology, Education Dept. of Guangdong Province, P.R. China
[2]Hong Kong polytechnic University
junzhang@ieee.org

ABSTRACT

The control parameters in evolutionary algorithms (EAs) have significant effects on the behavior and performance of the algorithm. Most existing parameter control mechanisms are based on either individual fitness or positional distribution of population. This paper proposes a parameter adaptation strategy which aims at evaluating the density distribution of population as well as both the fitness values comprehensively, and adapting the parameters accordingly. The proposed method modifies the values of *px* and *pm* based on the *relative cluster density* and the relative sizes of clusters containing the best and the worst individuals.

Categories and Subject Descriptors

I.2.8 [**Artificial Intelligence**]: Problem Solving, Control Methods, and Search – *heuristic methods.*

General Terms

Algorithms

Keywords

Evolutionary algorithms, genetic algorithm, parameter adaptation.

1. INTRODUCTION

Evolutionary algorithms (EAs) [1] are a class of population-based optimization techniques with a set of control parameters. It has been well established in the studies that the settings of control parameters in EAs have significant effects on the behavior and performance of the algorithm [3].

Various parameter control strategies have been developed to improve the efficacy and robustness of EAs [4]-[12]. According to the classification scheme in [3], parameter control strategies are classified into three categories, namely deterministic control [5], adaptive control [6]-[8], and self-adaptive control [9]. Based on the form of feedback utilized for adaptation, existing adaptive and self-adaptive control methods can be classified into two categories as follows.

Parameter adaptation mechanisms in the first category are based on the fitness values of individuals [7]-[9]. However, the fitness values of population can only reveal the state of evolution from one aspect. The positional distribution of individuals, which is related to premature convergence of EAs, is not considered in these strategies.

The second group of adaptation strategies adjust the parameters based on positional distribution of the population [8][10]-[12]. In contrast with the first category, adaptation methodologies in this class are competitive in maintaining the population diversity. However, these strategies do not take the fitness values into consideration.

In this paper, an adaptation strategy in the third category with the consideration of population density is proposed. The method aims at evaluating the fitness values and the population distribution comprehensively, and adapting the parameters accordingly. In order to outline the density distribution of population, a new variable termed *relative cluster density factor* (RCDF) is proposed. The RCDF cooperates with two other variables, i.e. the relative sizes of the cluster containing the best individual ($\boldsymbol{C_B}$) and the one containing the worst individual ($\boldsymbol{C_W}$), to reflect the population distribution from the aspect of population density. The proposed method first partitions the individuals into clusters according to their positional distribution. Rules for the adaptive adjustment of mutation probability *pm* and crossover probability *px* are based on the three variables. In every *M* generation, the values of *px* and *pm* are modified according to the rules.

2. Parameter Adaptation in AGA_DD

To reflect the distribution of individuals, the K-means algorithm is employed to partition the population into *K* different clusters. Denote the cluster containing the best individual to be $\boldsymbol{C_B}$, and the cluster containing the worst individual to be $\boldsymbol{C_W}$.

The ratio η between the mean distance between individuals in $\boldsymbol{C_B}$ and the mean distance between individuals in $\mathbf{P}_{gen}$ is calculated as

$$\eta = \frac{N \sum_{X \in C_B} \| X - \overline{X}_{CB} \|}{| C_B | \sum_{X \in P} \| X - \overline{X}_P \|}, \tag{4}$$

where *N* is the size of population, $\overline{X}_{CB}$ is the centroid of $\boldsymbol{C_B}$, and $\overline{X}_P$ is the centroid of the current population $\mathbf{P}gen$.

In our proposed method, the control of *px* and *pm* is based on the values of these variables. Eight rules for the adjustment of *px* and *pm* are tabulated in Table 1.

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Table 1. Rules for adjustment of *px* and *pm*

Rules for *px* and *pm*		
Rule (1,1,1)	**If** $\boldsymbol{C}_B$ is *largest*, $\boldsymbol{C}_w$ is *largest* , RCDF is *large*	*px→decrease* *pm→decrease*
Rule (1,1,0)	**If** $\boldsymbol{C}_B$ is *largest*, $\boldsymbol{C}_w$ is *largest* , RCDF is *small*	*px→increase* *pm→increase*
Rule (1,0,1)	**If** $\boldsymbol{C}_B$ is *largest*, $\boldsymbol{C}_w$ is *smallest*, RCDF is *large*	*px→decrease* *pm→increase*
Rule (1,0,0)	**If** $\boldsymbol{C}_B$ is *largest*, $\boldsymbol{C}_w$ is *smallest*, RCDF is *small*	*px→increase* *pm→--*
Rule (0,1,1)	**If** $\boldsymbol{C}_B$ is *smallest*, $\boldsymbol{C}_w$ is *largest,* RCDF is *large*	*px→increase* *pm→increase*
Rule (0,1,0)	**If** $\boldsymbol{C}_B$ is *smallest*, $\boldsymbol{C}_w$ is *largest,* RCDF is *small*	*px→increase* *pm→decrease*
Rule (0,0,1)	**If** $\boldsymbol{C}_B$ is *smallest*, $\boldsymbol{C}_w$ is *smallest,* RCDF is *large*	*px→increase* *pm→--*
Rule (0,0,0)	**If** $\boldsymbol{C}_B$ is *smallest*, $\boldsymbol{C}_w$ is *smallest,* RCDF is *small*	*px→increase* *pm→decrease*

3. EXPERIMENTS AND DISCUSSIONS

Experiments are conducted to study the performance and behavior of AGA_DD on a set of benchmark functions. The experimental results will be analyzed and discussed.

A set of 13 benchmark functions taken from the work of Yao *et. al* [13] are used to test the performance of AGA_DD.

Compared with the GAs with fixed parameters, the AGA_DD performs best among the five GAs on f_1-f_2, f_6, f_8-f_{13} and achieves second best performance on f_7 in terms of mean results, best results and standard deviations obtained. Particularly, when compared with GA(0.7, 0.015) which shares the same initial parameter settings with AGA_DD, the proposed algorithm significantly improves the results on most of the multimodal functions and separable unimodal functions. On the non-separable unimodal functions, AGA_DD succeeds in outperforming at least three of the five static GAs. To conclude, the proposed parameter adaptation scheme is effective in enhancing the algorithm performance and alleviating the efforts of parameter tuning in GA.

4. CONCLUSIONS

A parameter adaptation scheme for GA has been proposed. The parameter adaptation is based on the both the fitness values and the population distribution in the search space. Particularly, the relative population density around the best solution is taken into consideration, which implicitly reflects the fitness landscape.

For future work, the method can be extended to swarm intelligence algorithms [14] and discrete optimization problems [15].

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