An Improved Genetic Algorithm

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Abstract—In this paper, an improved genetic algorithm for multi-object optimization is proposed. Simulated annealing is used to local search in genetic algorithms. Furthermore, fuzzy reasoning is adopted to modify crossover probability and mutation probability according to characteristics of population in genetic algorithms instead of fixed parameters. And so, it can be convergence to global optimum quickly. This indicates that using this algorithm for multi-objective optimization problems has very strong utilitarian value.

Keywords—genetic algorithm; simulated annealing; multi-object optimization.

I. INTRODUCTION

Genetic Algorithms (GA) [1], [2] is a global search method that is inspired by the mechanics of natural evolution, is also a robust search and optimization techniques which are finding application in a number of practical problems. GA may be viewed as an evolutionary process wherein a population of solutions evolves over a sequence of generations. During each generation, the fitness of each solution is evaluated, and solutions are selected for reproduction based on their fitness. Selection embodies the principle of 'Survival of the fittest.' 'Good' solutions are selected for reproduction while 'bad' solutions are eliminated. The 'goodness' of a solution is determined from its fitness value. The selected solutions then undergo recombination under the action of the crossover and mutation operators. GA is characterized by the following components: an encoding for the feasible solutions to the optimization problem, a population of encoded solutions, a fitness function that evaluates the optimality of each solution and genetic operators that generate a new population from the existing population. In general, GA are stochastic search methods, which provide good solutions to complex optimization problems in relatively short times[3-6]. The scope of GA is related to those problems with high computational complexity, for which there are no alternatives to obtain the optimal solution in a relatively short limited time.

Simulated Annealing (SA) [7], [8] is also a search method that is based on the analogy with the physical annealing process of solids. GA and SA both require little knowledge of the problem itself and need not require that the search space is differentiable or continuous. Therefore, they can solve nonlinear multi-objective optimization problems that difficult using other techniques. GA and SA have been successfully used in a wide variety of areas such as function optimization, design optimization, image processing, schedule optimization, traveling salesman problem, neural networks etc.

GA has many disadvantages such as premature phenomenon, got into local optimization easily and time-consuming, so how to improve it is an important. However, a lot of literature is about the application of GA[9-12]. In this paper, an improved GA for the multi-objective optimization is proposed in order to solve the above mentioned problems. This is accomplished by using simulated annealing for local search and genetic algorithms for global search. Furthermore, fuzzy reasoning is adopted to modify crossover probability ($P_c$) and mutation probability ($P_m$) according to characteristics of population in genetic algorithms instead of fixed parameters. It can be convergence to global optimum by using a multimodal function to verify.

We will begin with introduction of combining GA with SA in section 2, the principle of using fuzzy reasoning to modify crossover probability and mutation probability in section 3, in section 4, the convergence of improved GA is verified by constructing a multimodal function. Conclusions are given in sections 5, respectively.

II. INTRODUCED SA INTO GA

SA algorithms(SAA) is a simulation of solid annealing process, which principle is that system state spontaneity change is always change along the free energy decreasing direction in the closed system with constant temperature via in exchange with ambient environment energy. System gets the balance state when free energy achieves a minimum. Boltzmann accepted criterion is used to accept new solution. SAA is controlled by cooling coefficient. Solved process list as follows:

Step1 Initialize annealing temperature $T_k$ (let $k = 0$), create random initial solution $x_0$;

Step2 Repeat the following operations under temperature $T_k$, until the balance state of temperature $T_k$ is achieved;

Step2.1 Create a new feasible solution $x'$ in solution domain $x$;

Step2.2 Calculate the difference value $\Delta f$ between evaluation function $f(x')$ of new solution $x'$ and $f(x)$ of old solution $x$;

Step2.3 Accept new solution according to probability $\min\{1, \exp (-\Delta f / T_k)\} > \text{random}[0,1]$, where random $[0,1]$ is a random number in $[0,1]$;
Step 3 Let $T_{k+1} = a T_k$, $k ← k+1$, where $a$ belong to (0,1), if convergence criterion is satisfied, then finished annealing process, otherwise, go to Step 2.

Solving process is optimization towards minimum, which is controlled by annealing temperature $T$. Meanwhile, bad solution is accepted by probability $\exp(-\Delta f / T_k)$, so SAA can converge to globally optimal solution and jump out local extremums as long as initial temperature is high and annealing process is slow enough. This paper introduces SAA into GA as local search for optimization. Its realized method is described as follows.

This algorithm will begin with using GA as global search, and then use SAA to adjust gene population. Its emphasis is local search. It can not only add object constraint condition but also improve the evolution speed of GA. Objective function’s optimal solution with multi-condition constraint can be obtained by less iterating times.

III. THE PRINCIPLE OF USING FUZZY REASONING IN GA

In this paper, fuzzy reasoning is adopted to modify $P_c$ and $P_m$ according to characteristics of population in GA, rather than using fixed parameters. Its principle is shown in figure 1.

\[
\begin{align*}
A &= \frac{f_{\text{max}} - \bar{f}}{f_{\text{max}} - f_{\text{min}}} \\
B &= \frac{f_{\text{max}} - f_i}{f_{\text{max}} - f_{\text{min}}} \\
C &= \frac{f_i - f_j}{f_{\text{min}} - f_{\text{min}}} \\
D &= \frac{x_i - x_j}{x_{\text{max}} - x_{\text{min}}}
\end{align*}
\]

where $f_{\text{max}}$ = maximum of fitness function in the current population; $f_{\text{min}}$ = minimum of fitness function in the current population; $\bar{f}$ = average value of fitness function in the current population; $f_i, f_j$ is separately a arbitrary individual fitness function in the current population; $x_{\text{max}} = \text{maximum individual value in the current population}$; $x_{\text{min}} = \text{minimum individual value in the current population}$; and $x_i, x_j$ is an arbitrary individual value in the current population.

And then the input A, B, C and D are normalised to [0, 1], output $P_c$ is normalised to [0.1, 0.9] and output $P_m$ is normalised to [0.01, 0.65], which becomes their domain for fuzzification. The term set for all the variables are taken as {PS, PM, PB}. The fuzzy variables’ membership functions are shown in Figure 2.

![Figure 2. Fuzzy variables’ membership function plots.](image)

Figure 2. Fuzzy variables’ membership function plots.

The obtained fuzzy control rules for control parameter $P_c$ in the next population (according to maintaining population’s multiformity, avoiding got into local optimization) are summarized in Table 1.

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| $B$ is a PS value. |

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| $B$ is a PM value. |

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| $B$ is a PB value. |

The obtained fuzzy control rules for control parameter $P_m$ in the next population (according to maintaining population’s multiformity, avoiding got into local optimization) are summarized in Table 2.
Table 2. Rule Matrix of Fuzzy Controller for $P_m$.

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IV. THE CONVERGENCE OF IMPROVED GA

 Constructed a multimodal function:

$$f(x) = -15 \times e^{-0.08 \left( \sum_{j=1}^{n} x_j \right)} - e^{-x_{\text{min}(2n)}} + 17.7183$$

Consider Equation 5 with $n = 2$, its curve is shown in figure 3.

Equation 5 with $n = 2$ is a typical multimodal function. Its theoretical minimum is (0, 0, 0). The result of solving this problem by means of this GA with a population $n = 100$, an initial crossover probability $P_c = 0.9$, and an initial mutation probability $P_m = 0.1$ is shown in figure 4. (0.0000, 0.0001, 0.0001139) is the searching minimum by using this GA. This result clearly indicates that it can converge to global optimum quickly.

V. CONCLUSIONS

This paper presented the an improved genetic algorithm, which combine SA with GA, and use fuzzy reasoning to adjust crossover probability and mutation probability according to characteristics of population and individual in GA instead of fixed parameters. Above research indicates that using this algorithm for multi-objective optimization has very strong utilitarian value.

REFERENCES


Dr. Yan Gangfeng is presently working in School of Electronic Information Engineering, Chengdu University, ChengDu, Sichuan, China. His areas of interest are stochastic signal processing, control technology, optimization algorithm, numerical analysis, and embedded system. He now has twenty papers published.