Evolutionary algorithm based on schemata theory

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Abstract The stochastic schemata exploiter (SSE), which is one of the evolutionary algorithms based on schemata theory, was presented by Aizawa. The convergence speed of SSE is much faster than simple genetic algorithm. It sacrifices somewhat the global search performance.

This paper describes an improved algorithm of SSE, which is named as cross-generational elitist selection SSE (cSSE). In cSSE, the use of the cross-generational elitist selection enhances the diversity of the individuals in the population and therefore, the global search performance is improved.

In the numerical examples, cSSE is compared with genetic algorithm with minimum generation gap (MGG), Bayesian optimization algorithm (BOA), and SSE. The results show that cSSE has fast convergence and good global search performance.

Keywords stochastic schemata exploiter, cross-generational elitist selection, minimal generation gap, Bayesian optimization algorithm

1 Introduction

In actual complicated optimization problems, it is often difficult to find a global optimum solution in admissible computing time. Therefore, in industrial problems, we have to find quasi-optimum solution in admissible computing time. For this purpose, evolutionary computations (ECs) are very attractive.

There are several algorithms in the EC family: genetic algorithm (GA), evolutionary strategy (ES), genetic programming (GP), and so on. Stochastic schemata exploiter (SSE), which was presented by Aizawa [1], is also classified into one of the ECs. Although the basic concept of SSE is from the GA, its algorithm is very different from GA. In GA, the individuals are generated randomly to construct a population. After estimating the fitness of individuals, parents are selected from the population according to the fitness value. Offsprings are generated from the parents by applying genetic operators such as the mutation, the crossover, and so on. SSE algorithm also starts from the population of randomly generated individuals. After estimating the fitness of individuals, sub-populations are generated from the whole population according to semi-order relationship of the sub-populations. Common schemata are extracted from the sub-populations and offsprings are generated from the common schemata. Since SSE can spread better schemata over the whole population faster than the GA, the convergence speed of SSE is also faster than that of the GA. However, SSE sometimes converges to a not global optimum solution but local one.

The aim of this study is to improve the search performance of SSE without sacrificing the convergence speed. For this purpose, this paper presents cross-generational elitist selection SSE (cSSE), in which the cross generational elitist selection is introduced to the original SSE. The use of the cross-generational elitist selection enhances the diversity of the population and therefore, the global search performance is improved. In the numerical examples, cSSE is compared with genetic algorithm with minimum generation gap (MGG), Bayesian optimization algorithm (BOA), and SSE in some numerical examples. The results show that cSSE has fast convergence and good global search performance.

2 Background

2.1 Genetic algorithm

Genetic algorithm (GA) was first presented by Holland in 1975 [2]. The GA, which is the algorithm to mimic natural
evolution, is applied widely to several problems such as optimization, adaptation and learning. The basic algorithm of the GA is often called simple genetic algorithm (SGA) [3].

The SGA algorithm is illustrated in Fig. 1. First, individuals are generated randomly to construct a population. After estimating the fitness of individuals, parents are selected from the population according to the fitness value. Offsprings are generated from them by using the mutation, the crossover, and so on. The processes are repeated until the convergence criterion is satisfied.

2.2 Minimum generation gap

The search performance of the SGA depends on early convergence and evolutionary stagnation [4,5]. Early convergence means that all individuals gather to same local optimum solutions at early generation and therefore, the global (real) optimum solution cannot be found. The evolutionary stagnation means that the convergence speed slows down at final generations. For overcoming these problems, a new generational alternation model, minimal generation gap (MGG), was presented by Satoh et al. [6]. Several numerical results show that the GA with MGG can find global solutions while its convergence speed is not so fast [7]. In this study, GA with MGG is adopted for confirming the performance of cSSE final solutions.

2.3 Bayesian optimization algorithm

Estimation of distribution algorithm (EDA) is also one of evolutionary computations. The EDA searches a solution according to a stochastic model learned from the information of the better solutions in the population. Since offsprings are generated from the stochastic model, the selection, the crossover, and the mutation operations are not necessary in EDA.

Bayesian optimization algorithm (BOA), which is one of the EDA, was presented by Pelikan et al. [8]. In BOA, the Bayesian network plays as the stochastic model of EDA. The convergence speed of BOA is much faster than that of SGA. In this study, BOA is adopted to confirm the convergence speed of cSSE.

2.4 Stochastic schemata exploiter

The algorithm of SSE is illustrated in Fig. 2.

After estimating the fitness of individuals, these are ranked according to the descending order of their fitness. Sub-populations are generated according to the semi-order relation of sub-populations. Common schemata are extracted from the individuals in each sub-population. Since schemata are composed of “0”s, “1”s, and “∗”s, new individuals are generated from the schemata by randomly replacing “∗” with “0” or “1”. The number of the sub-populations is usually equal to population size. Therefore, the population size is kept to be invariant.

2.5 Cross generational elitist selection SSE

Since SSE can spread good schemata over a whole population quickly, the convergence speed is faster than GA. However, the diversification of individuals in the population is quickly lost and therefore the search process is sometimes attracted to a local solution.

The cross-generational elitist selection SSE (cSSE) is designed such that the diversification of individuals in the population is lost more slowly without sacrificing the convergence speed of the original SSE. For the purpose, the cSSE adopts the following processes: