Chapter 6
Co–Evolutionary Algorithms Based on Mixed Strategy

Wei Hou
Harbin Engineering University & Northeast Agricultural University, China

HongBin Dong
Harbin Engineering University, China

GuiSheng Yin
Harbin Engineering University, China

ABSTRACT

Inspired by evolutionary game theory, this paper modifies previous mixed strategy framework, adding a new mutation operator and extending to crossover operation, and proposes co-evolutionary algorithms based on mixed crossover and/or mutation strategy. The mixed mutation strategy set consists of Gaussian, Cauchy, Levy, single point and differential mutation operators; the mixed crossover strategy set consists of cuboid, two-points and heuristic crossover operators. The novel algorithms automatically select crossover and/or mutation operators from a given mixed strategy set, and improve the evolutionary performance by dynamically utilizing the most effective operator at different stages of evolution. The proposed algorithms are tested on a set of 21 benchmark problems. The results show that the new mixed strategies perform equally well or better than the best of the previous evolutionary methods for all of the benchmark problems. The proposed MMCGA has shown significant superiority over others.

INTRODUCTION

Several mutation operators have been proposed in evolutionary programming (EP), e.g., Gaussian, Cauchy, Levy, Single Point and Differential mutations. Experiments show that Gaussian muta-

tion has a good performance for some unimodal functions and multimodal functions with only a few local optimal points; Cauchy mutation works well on multimodal functions with many local optimal points; Levy mutation can lead to a large variation and a large number of distinct values in evolutionary search, and is said to be more general and flexible because of its scaling parameter;

Single Point mutation is based on the coordinate ordering for each solution, it can converge to global optimum more than other algorithms; DE is arguably one of the most powerful stochastic real-parameter optimization algorithms in current use and it shows strikingly better performance as compared to classical evolutionary algorithms (EAs) on numerical benchmarks.

According to no free lunch theorem, none of mutation operators is efficient in solving all optimization problems, but only in a subset of problems. Overall performance of the EP can be improved by using different mutation operators simultaneously or by integrating several mutation operators into one algorithm or by adaptively controlled usage of mutation operators. An early implementation is a linear combination of Gaussian and Cauchy distributions (Chellapilla, 1998). This combination can be viewed a new mutation operator, whose probability distribution is a convolution of Gaussian and Cauchy's probability distributions. IFEP (Yao, Liu & Lin, 1999) adopts another technique: each individual implements Cauchy and Gaussian mutations simultaneously and generates two individuals; the better one will be chosen in the next generation. Lee (2004) developed the idea of IFEP further into mixing Levy distribution with various scaling parameters. SPMEP is superior to both CEP (Fogel, Owens & Walsh, 1966) and FEP (Yao, Liu & Lin, 1999) for many multimodal and high-dimensional functions. The mixed mutation strategy integrates several mutation strategies into one algorithm within one population in our previous work. An individual can adjust its mixed strategy based on the payoffs of strategies and select a mutation operator with higher probability to adapting different operators to different stages of evolution. An ensemble approach is where each mutation operator has its associated population and every population benefits from every function call (Mallipeddi & Suganthan, 2010).

The crossover is the most significant operator to generate dissimilar individuals which may be possible solutions to the problem under consider-

ation. A mixed strategy evolutionary programming has been proposed in our previous work, achieving good performances on numerical optimization. In this work, we add the differential mutation operator into the mixed mutation strategy in our previous work and extend the mixed strategy to crossover operation. We discuss four variations of evolutionary algorithm based on the mixed crossover or/and mutation strategy and their performances on numerical optimization.

The work presented in this paper is organized as follows. The next section presents the framework of evolutionary algorithm based on mixed strategy. The modified mixed mutation strategy by adding differential mutation operator into the framework is discussed and a novel mixed crossover strategy is proposed. The automated operator selection techniques based on mixed crossover and mutation strategies is presented, as well as the experimental design and the performance of each algorithm.

THE FRAMEWORK OF EVOLUTIONARY ALGORITHM BASED ON MIXED STRATEGY

In theory mixed strategies (Dutta, 1999; Ficici, Melnik & Pollack, 2000) have some potential advantages over pure strategies (He & Yao, 2005). Individuals are regarded as players in a game. Each individual will choose a crossover or mutation strategy from its strategy set based on a selection probability and generate an offspring by this strategy.

The mixed strategy is described as follows: at each generation, an individual chooses one mutation strategy s from its strategy set based on a selection probability $p(s)$. This probability distribution is called a mixed strategy distribution in the game theory. The key question is to find out a good, if possible an optimal, mixed probability $p(s)$ for every individual. This mixed distribution may be changed over generations.

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