



## **Chapter XV**

# **The Effect of Multi-Parent Recombination on Evolution Strategies for Noisy Objective Functions**

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### **ABSTRACT**

*In this chapter we apply  $(\mu / \mu, \lambda)$ -ES to noisy test functions, in order to investigate the effect of multi-parent versions of both intermediate recombination and discrete recombination. Among the many formulations of ES, we test three in particular; Classical-ES (CES), i.e., Schwefel's original ES (Schwefel, 1995, Bäck, 1996); Fast-ES (FES), i.e., Yao and Liu's extended ES (Yao & Liu, 1997); and Robust-ES (RES), i.e., our extended ES (Ohkura, 2001). Computer simulations are used to compare the performance of multi-parent versions of intermediate recombination and discrete recombination in CES, FES and RES. We saw that the performance of the  $(\mu / \mu, \lambda)$ -ES algorithms depended on the particular objective functions. However, the FES and RES algorithms were seen to be improved by multi-parent versions of discrete recombination applied to both object parameters and strategy parameters.*

## INTRODUCTION

Noise is a common phenomenon in many real-world problems. For example, in the field of information engineering, any signal returned from the real world usually includes a significant amount of noise. Also in the field of Evolutionary Robotics (Harvey et al., 1997), simulation models are developed by taking noise into account in order to decrease the gap between simulated and real-world robot performance (Jacobi et al., 1995). In such cases, Evolutionary Algorithms (EAs) work well even in the presence of noise.

EAs have three main approaches, namely Evolutionary Programming (EP), Evolution Strategies (ES) and Genetic Algorithms (GAs). ES has several formulations (Schwefel, 1995, Bäck, 1996).  $(\mu/\rho, \lambda)$ -ES is the general form for real-valued parameter optimization problems, in which  $\mu$  parents generate  $\lambda$  offspring through recombination and mutation at each generation, and the best  $\mu$  offspring are selected deterministically from the  $\lambda$  offspring to replace the current set of parents.  $\rho$  determines the number of parents to form one new offspring, with the case where  $\rho > 2$  known as multi-recombination (Beyer, 2001).

In  $(\mu/\rho, \lambda)$ -ES, Beyer (1995) theoretically investigated the case of  $\rho = \mu$  for the sphere function, finding a  $\lambda$ -fold speedup compared to ESs without recombination. For ESs, each individual has a pair of real-valued vectors, i.e., the object parameters and strategy parameters, with strategy parameters roughly determining the size of mutation applied to object parameters. Beyer used recombination only on the object parameters, however it is necessary for ES researchers to investigate the effect of recombination on not only object parameters but also strategy parameters, both empirically and theoretically.

There are two popular recombination operators, namely intermediate recombination and discrete recombination. Many ES researchers (Bäck & Schwefel, 1993, Bäck & Eiben, 1998; Eiben & Bäck, 1998) often apply only intermediate recombination to strategy parameters due to Schwefel's general recommendations (Schwefel, 1995). However, Chang et al. (2001) experimentally investigated multi-parent versions of both intermediate recombination and discrete recombination on strategy parameters, and showed the advantages of not only intermediate recombination but also discrete recombination. They used 11 standard test functions and tested ES with Gaussian mutation, or Classical-ES (CES). However, the test functions they used did not incorporate noise. Thus we must investigate the performance of ESs with multi-parent recombination on noisy test functions in order to apply ESs to real world optimization problems.

In this chapter we apply  $(\mu/\mu, \lambda)$ -ES to noisy test functions, in order to investigate the effect of multi-parent versions of both intermediate recombination and discrete recombination. Among the many formulations of ESs, we test three in

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