Chapter 7.22
Gene Expression Programming and the Evolution of Computer Programs

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ABSTRACT

In this chapter an artificial problem solver inspired in natural genotype/phenotype systems — gene expression programming — is presented. As an introduction, the fundamental differences between gene expression programming and its predecessors, genetic algorithms and genetic programming, are briefly summarized so that the evolutionary advantages of gene expression programming are better understood. The work proceeds with a detailed description of the architecture of the main players of this new algorithm (chromosomes and expression trees), focusing mainly on the interactions between them and how the simple yet revolutionary structure of the chromosomes allows the efficient, unconstrained exploration of the search space. And finally, the chapter closes with an advanced application in which gene expression programming is used to evolve computer programs for diagnosing breast cancer.

EVOLUTIONARY ALGORITHMS IN PROBLEM SOLVING

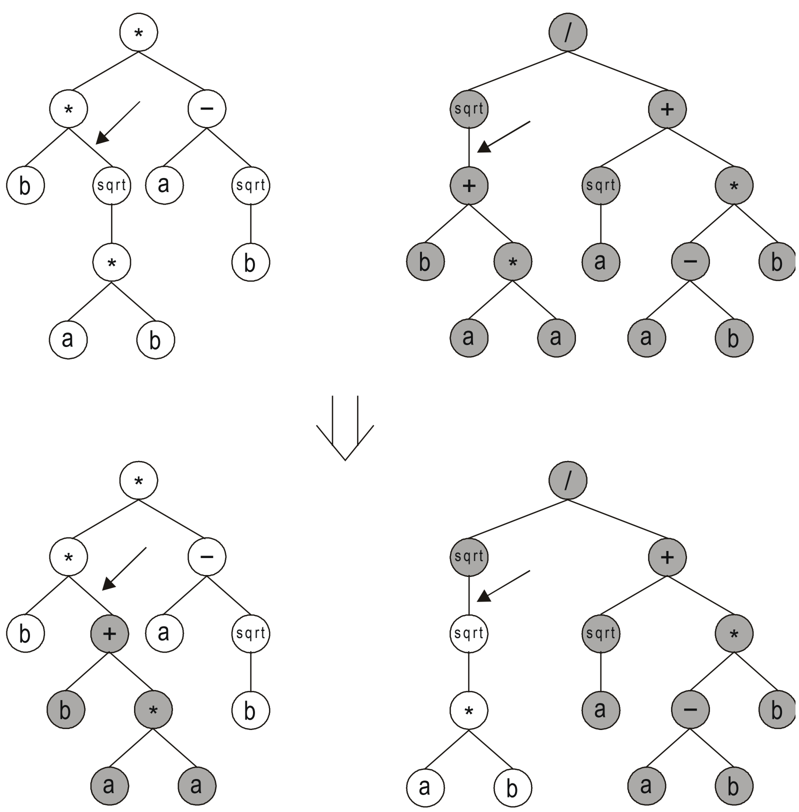
The way nature solves problems and creates complexity has inspired scientists to create artificial systems that learn by themselves how to solve a particular problem. The first attempts were done in the 1950s by Friedberg (1958; Friedberg et al., 1959), but ever since highly sophisticated systems have been developed that apply Darwin's ideas of natural evolution to the artificial world of computers and modeling. Of particular interest to this work are the Genetic Algorithms (GAs) and the Genetic Programming (GP) technique, as they are the predecessors of Gene Expression Programming (GEP), the most recent development in evolutionary computation and the theme of this chapter. A brief introduction to these three techniques is given below.

Genetic Algorithms

Genetic algorithms were invented by John Holland in the 1960s and they also apply biological evolution theory to computer systems (Holland, 1975). Like all evolutionary computer systems, GAs are an oversimplification of biological evolution. In this case, solutions to a problem are usually encoded in strings of 0s and 1s (chromosomes), and populations of such strings (individuals or candidate solutions) are used in order to evolve a good solution to a particular problem. From generation to generation candidate solutions are reproduced with modification and selected according to fitness. Modification in the original genetic algorithm was introduced by the genetic operators of mutation, crossover, and inversion.

It is worth pointing out that GAs' individuals consist of naked chromosomes or, in other words, GAs' individuals are simple replicators. And like all simple replicators, the chromosomes of genetic algorithms function simultaneously as genotype and phenotype: they are both the object of selection and the guardians of the genetic information that must be replicated and passed on with modification to the next generation. Consequently, the whole structure of the replicator determines the functionality and, therefore, the fitness of the individual. For instance, in such systems it would not be possible to use only a particular region of the replicator as a solution to a problem: The whole replicator is always the solution: nothing more, nothing less.

Figure 1. Tree crossover in genetic programming (arrows indicate the crossover points)



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