STATE OF THE ART IN EVOLUTION STRATEGIES

by THOMAS BÄCK†, BORIS NAUJOKS‡

†NuTech Solutions GmbH
Martin-Schmeisser-Weg 15
D-44227 Dortmund
Email: Thomas.Baeck@nutechsolutions.com
and
Leiden Institute for Advanced Computer Science
Niels Bohrweg 1
NL-2333 CA Leiden

‡Center for Applied Systems Analysis (CASA)
Informatik Centrum Dortmund (ICD)
Joseph-von-Fraunhofer-Str. 20
D-44227 Dortmund
Email: naujoks@icd.de

Abstract

Evolution strategies are one of the main paradigms in the field of *evolutionary computation*, focusing on algorithms for adaptation and optimization which are gleaned from the model of organic evolution.

The report puts its emphasis on algorithmic and application-oriented aspects of evolution strategies. The algorithmic aspects include an overview of all components of a modern (μ,λ)-strategy and a detailed explanation of the concept of *strategy parameter self-adaptation*, which is considered to be the main distinguishing feature between evolution strategies and genetic algorithms. The working principles of self-adaptation are explained in detail in this report.

A number of recent variations of the basic evolution strategy, including alternatives for the self-adaptation method, a control mechanism for the population size, the introduction of hierarchies of evolution strategies, and the principle of individual aging in the (μ,κ,ρ,λ)-strategy are presented in the following section.

The report concludes by giving an outline of the perspectives of evolution strategies by discussing its technological future with a focus on the economic potential by industrial applications of these algorithms. This outline might serve as a technological roadmap for the exploitation of these techniques within a ten year timeframe.

1 A BRIEF HISTORY

Evolution Strategies are a joint development of Bienert, Rechenberg and Schwefel, who did preliminary work in this area in the 1960s at the Technical University of Berlin (TUB) in Germany. First applications were experimental and dealt with hydrodynamical problems like shape optimization of a bended pipe [24], drag minimization of a joint plate [28], and structure optimization of a two-phase flashing nozzle [45][1]. Due to the impossibility to describe and solve such optimization problems analytically or by using traditional methods, a simple algorithmic method based on random changes of experimental setups was developed. In these experiments, adjustments were possible in discrete steps only, in the first two cases (pipe and plate) by changing certain joint positions and in the latter case (nozzle) by exchanging, adding or deleting nozzle segments. Following observations from nature that smaller mutations occur more often than larger ones, the discrete changes were sampled from a binomial distribution with prefixed variance. The basic working mechanism of the experiments was to create a mutation, adjust the joints or nozzle segments accordingly, perform the experiment and measure the quality criterion of the adjusted construction. If the new construction happened to be better than its predecessor, it served as basis for the next trial. Otherwise, it was discarded and the predecessor was retained. No information about the amount of improvements or deteriorations was necessary. This experimental strategy led to unexpectedly good results both for the bended pipe and the nozzle.

Schwefel was the first who simulated different versions of the strategy on the first available computer at TUB, a Zuse Z23 [35], later on followed by several others who applied the simple Evolution Strategy to solve numerical optimization problems. Due to the theoretical results of Schwefel's diploma thesis, the discrete mutation mechanism was substituted by normally distributed mutations with expectation zero and given variance [35]. The resulting *two membered* ES works by creating one n-dimensional real-valued vector of object variables from its parent by applying mutation with identical standard deviations to each object variable. The resulting individual is evaluated and compared to its parent, and the better of both individuals survives to become parent of the next generation, while the other one is discarded. This simple selection mechanism is fully characterized by the term (1+1)-selection.

For this algorithm, Rechenberg developed a convergence rate theory for $n \gg 1$ for two characteristic model functions, and he proposed a theoretically confirmed rule for changing the standard deviation of mutations (the 1/5-*success rule*) [29].

Obviously, the (1+1)-ES did not incorporate the principle of a population. A first *multi-membered* Evolution Strategy or (μ+1)-ES having $\mu > 1$ was also designed by Rechenberg to introduce a population concept. In a (μ+1)-ES μ parent individuals recombine to form one offspring, which after being mutated eventually replaces the worst parent individual — if it is better (extinction of the worst). Mutation and adjustment of the standard deviation was realized as in a (1+1)-ES, and a recombination mechanism as explained

[1] This experiment is one of the first known examples of using operators like gene deletion and gene duplication, i.e. the number of segments the nozzle consisted of was allowed to vary during optimization.