Using Gene Deletion and Gene Duplication in Evolution Strategies

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ABSTRACT

Self-adaptation of the mutation strengths is a powerful mechanism in evolution strategies (ES), but it can fail. As a consequence premature convergence or ending up in a local optimum in multi-modal fitness landscapes can occur. In this article a new approach controlling the process of self-adaptation is proposed. This approach combines the old ideas of gene deletion and gene duplication with the self-adaptation mechanism of the ES. Gene deletion and gene duplication is used to vary the number of independent mutation strengths. In order to demonstrate the practicability of the new approach several multi-modal test functions are used. Methods from statistical design of experiments and regression tree methods are applied to improve the performance of a specific heuristic-problem combination.

Categories and Subject Descriptors

I.6 [**Simulation and Modeling**]: Model Development

General Terms

Algorithms

Keywords

Evolution strategy, self-adaptation, gene duplication

1. INTRODUCTION

In modern synthesis of evolutionary theory, gene duplication emerged as a major force. In particular, redundant gene loci created by gene duplication are permitted to accumulate formerly forbidden mutations and emerge then as additional gene loci with new functions. The first ES using operators like gene duplication and gene deletion can be found in Schwefel's investigations of a nozzle for a two-phase flow. This leads to surprising good results. Unfortunately, most of these variable-length approaches are extremely application-oriented. Perhaps the most important reason for the application-oriented design is the restrictive fixed-length and fixed-position representation of the solutions that are used in many search heuristics. In this poster an application independent approach is presented. Starting from the idea of introducing gene duplication and gene deletion into the mechanism of self-adaptation of an ES, additional genetic operators varying the number of used independent endogenous strategy parameters are introduced to generate a satisfactory self-adaptation in various fitness landscapes.

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2. IMPLEMENTATION DETAILS

The multi-membered ES with σ-self-adaptation is used. In general, the implementation of the self-adaptation mechanism depends on the kind and the number of strategy parameters to be adapted. Given an individual $\vec{a} = (\vec{x}, \vec{\sigma}, \vec{\alpha})$, where $\vec{x}$ is the vector of objective variables, $\vec{\sigma}$ holds the set of mutation strengths and $\vec{\alpha}$ denotes the rotation angles. Each individual may include one up to $N(N+1)/2$ endogenous strategy parameters. For the case $1 < n_\sigma < N$ the mutation strengths $\sigma_1, \ldots, \sigma_{N-1}$ are coupled with the corresponding object variables and σ_N is used for the remaining ones. The number of rotation angles n_α depends directly on n_σ or is explicit set to 0. The new deletion and duplication operator work on the set of mutation strengths (n_σ) only. The additional variation operators are defined as follows:

Duplication Operator: With a predefined duplication probability ($dup = 0.028$) a duplication may occur if $n_\sigma < N$. The duplicated mutation strength is added then at the end of $\vec{\sigma}$. The rate of gene duplication is taken from nature.

Deletion Operator: Vice versa a predefined deletion probability ($del = 0.028$) is used in order to delete the last mutation strength in n_σ if $n_\sigma > 1$ or not. The deletion of the last mutation strength is used because of their direct coupling with the rotation angles.

3. EXPERIMENTAL SETUP & RESULTS

The problem of choosing nearly optimal parameter settings for a given heuristic-problem combination is essential for the success of a search process. Practitioners often use so-called standard parameters. Experiences from the last four decades show that each heuristic-problem combination requires a specific parameterization. Manifold methods are proposed to tackle this problem. In this study, tree based methods, fractional factorial designs as well as classical regression analysis are used to achieve good parameter settings and to analyze the obtained results. The modified adaptation technique is demonstrated on five models: The Sphere, the Double Sum, the generalized Rastrigin, the Ackley and the Fletcher-Powell function.

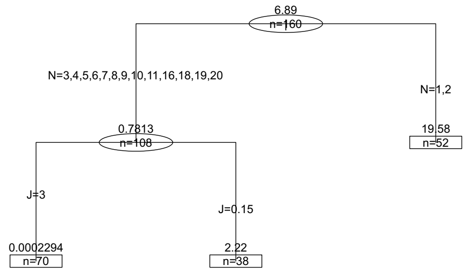

Figure 1: Pruned regression tree for the modified ES optimizing a 20-dimensional Ackley function.

3.1 Experimental Results

The following experiments were performed to investigate the question if the new duplication and deletion operator improve the performance of an ES when optimizing multi-modal fitness functions. Therefore it is a common practice to compare the performance of the new algorithm including the additional operators with the standard implementation of the original algorithm. In order to ensure a relative fair comparison, both algorithms have to be tuned on the given heuristic-problem combination at first.

3.1.1 A Simple Tuning Step

First experiments, based on regression tree and classical regression methods, were performed to find nearly optimal parameter settings for both algorithms. As an example, Fig. 1 shows the pruned tree of the fitness values from the ackley function with correlated mutations using the modified ES. The first split partitions the $N = 160$ observations into groups of 108 (left node) and 52 (right node) observations. The left group contains experimental runs with a great number of mutation strengths $N = \{3, \ldots, 20\}$ and an average fitness value of 0.7831, and the right node contains all experimental runs, where the number of used mutation strengths remains very small $N = \{1, 2\}$ with an average fitness value of 19.58. Following the tree down to the node with the smallest average fitness value $2.294E-4$ the regression tree indicates that a greate (3) initial value of the mutation strength (J) is significant for the success of the evolution runs. After several tuning steps the tuned parameter settings for the heuristic-problem combination reads:$\mu = 20$, $\lambda = 120$, $\kappa = +\infty$, $Recomb_x$ = intermediate $Recomb_\sigma$ = discrete, $Recomb_\alpha$ = true, $\rho = 2$ $\beta = 0.08725$, $N_\sigma = 3$, $\sigma_{init} = 3.0$, $dup = 0.001$, $del = 0.001$ and $\mu = 20$, $\lambda = 60$, $\kappa = 1$, $Recomb_x$ = discrete $Recomb_\sigma$ = intermediate, $Recomb_\alpha$ = true, $\rho = 2$ $\beta = 0.08725$, $N_\sigma = 3$, $\sigma_{init} = 3.0$, for the modified and the standard ES respectivley.

3.1.2 Comparisons

A comparison of the tuned algorithms was performed in this section. Fig. 2 shows that on a 20-dimensional Ackley function, the modified ES (DupDel) outperforms the standard ES in a significant manner. The arithmetic mean of ten independent runs with correlated mutations is depicted, respectively. From 10 independent experiments all runs of DupDel are able to reach the global attractor area. In contrast to this, the standard ES is not able to guide the population through the multi-modal fitness landscape. Similar results can be observed in all other test functions.

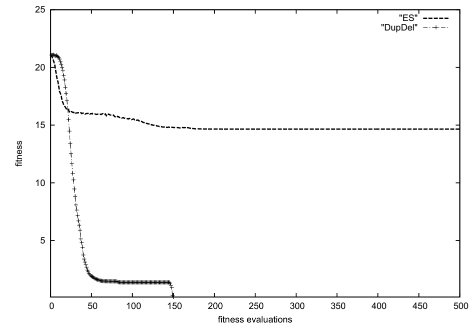

Figure 2: Arithmetic mean of 10 runs optimizing the ackley model with correlated mutations.

Table 1: Optimizing a 20-dimensional sphere model.

Model	median	mean fitness	variance
$ES_{without}$	$7.357e{-}77$	$1.022e{-}76$	$4.72442e-153$
$DupDel_{without}$	$3.110e{-}77$	$2.913e{-}77$	$3.753419e-155$
ES_{with}	$6.227e{-}77$	$6.287e{-}77$	$9.179366e-155$
$DupDel_{with}$	$2.895e{-}77$	$3.009e{-}77$	$3.664180e-155$

3.1.3 Discussion

In the last section it was shown that it could be favorable to use gene deletion and gene duplication from nature to solve multi-modal problems - but why? Looking at the duplication operator, a duplication take place with a probability of $dup = 0.028$ or 0.001. In case of $N_\sigma = 1$, adding a second strategy variable the first endogenous variable controls the first objective variable only, the second controls all the rest. In the early stage of the optimization this will lead to relative great jumps in the fitness landscape. The more duplication and the greater the initial mutation strengths the greater the fluctuations in the fitness values. In multi-modal landscapes this effect could be high enough to guide a hole population out of a local optimum. On the other side it must be also considered that this effect, which is favorable in the early stage of the evolution run, is counterproductive for the end, when the global attractor area is achieved. In many test functions when the global attractor area is achieved, the special case of a sphere function can be found. Therefore, both heuristics were set up on a 20-dimensional sphere function. Table 1 shows the obtained results.

Despite of duplication and deletion, the modified ES is able to adapt the global optima in the same accuracy as the standard ES. The reasons could be found in the progress of the optimization run itself. During the run, the self-adaptation process leads to smaller and smaller standard deviations, so if a duplication or deletion occurs, the noise will become smaller and smaller. Differences between both models seem to have vanished at the end of the evolution run.

The results show that varying the number of independent mutation strength the risk of failure of the commonly used self-adaptation mechanism can be reduced in a significant manner. Further investigations have shown that the modified strategy is able to find global optima in the same quickly and accurately way.