Using Predators and Preys in Evolution Strategies

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ABSTRACT

This poster presents an evolution strategy for single- and multi-objective optimization. The model uses the predator-prey approach from ecology to scale between both cases. Furthermore the main issue of adaptation working for single- and multi-objective problem-instances equally is discussed. Particular, the well proved self-adaptation mechanism for the mutation strengths in the single-objective case is adopted for the multi-objective one. This self-adaptation process is supported by a new strategy of competition between predators and preys. Six test functions are used to demonstrate the practicability of the model.

Categories and Subject Descriptors

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

General Terms

Algorithms

Keywords

Predator-Prey, multi criterion, Evolution strategy

1. INTRODUCTION

In modern synthesis of evolutionary theory their is a broad agree upon the hypothesis that species evolve by increasing their adaptation to the environment where they live. Theses adaptation process takes place by variation at the genotype level and by developing new strategies of competition with other species. While the particular attention is payed on the genotype level in single objective optimization as well as in the multi-objective case, research focusing on the level of species interaction remained rare. These studies have show that a predator-prey model is effective in the field of multi-objective optimization problems (MOP). Their crucial advantages can be summarized into two main arguments: (1) Scalability between single-objective and multi-objective optimization, and (2) the consequential conduction of the inherent parallel alignment of each population based approach. Scalability between single-objective optimization and multi-objective optimization is achieved by adding further predator species into the selection process only. No further modifications are necessary. The hope and the aim of these approaches is the design of a heuristic for single- and multi-objective problems at last. In the second, Laumanns et al. has designed his model in an asynchronous and parallel manner. Most models from ecology show that individuals interact in time and space within their own specie as well as with other species. Laumanns was the first, who has mimicked successfully both decisive factors from ecology in order to preserve diversity in the current population.

This poster takes up the inspiration of the predator-prey models. Starting from the idea of using an evolution strategy (ES) as the basic underlying search heuristic the question that has to be answered is: "How an ES has to be modified or parameterized to solve MOP, too".

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2. THE PREDATOR-PREY MODEL

In the following a predator-prey model for multi-objective optimization is presented. Based on the underlying search heuristic – an evolution strategy (ES) – the necessary modifications to solve MOP are sketched.

2.1 Choice of Population Structure

In literature it has been shown that the use of spatial population structures is favorable to achieve a diverse set of non-dominated solutions. In general the exchange from panmictic operating variation and selection operators through local ones are the main feature of the spatial structures. This will be modeled in this approach by dividing of the global population into subpopulations (demes). The number of demes is a new exogenous parameter (N_{deme}). Starting from a global definition of a $(50 \overset{+}{,} 500)$-ES the 50 parent individuals are divided into N_{deme} uniform demes, which have constant size during the evolutionary run.

Recombination: Recombination takes place within these demes only. No migration between demes is allowed. The number of offsprings is defined in the same manner as the number of parents. For example, in the case of $N_{deme} = 2$ the global population is divided into two uniform demes. Within each deme a $(25 \overset{+}{,} 250)$-ES is performed.

Selection: The number of predators, which are used in the evolution is defined by a maximum number of predators per objective (N_{pred1}, and N_{pred2}, ...). Selection is performed by an uniformly distributed selection from the amount of predators. That defines how many predators perform in the specific deme the selection. In this way for every deme the composition of the pack of predators for the actual deme is defined anew. As long as the number of individuals in the specific deme is greater than the predefined number of parents, selection take place.

Mutation and Step Size Control: The self-adaptive mutation mechanism from ES is used. The only change is concerned to lower bounds of the mutation strength.

The lower bound of the mutation strength is defined for each individual by the formula:

$$\epsilon_{relative} = (bestPrey1 + bestPrey2)/2, \qquad (1)$$

where *bestPrey1* denotes to the mutation strength of the current best prey for objective 1 and *bestPrey2* denotes to the mutation strength of the current best prey for objective 2. In this way the controlling mechanism for the mutation strength is no longer restricted by an arbitrary fix lower bound, but on a bound, which value is defined by the controlling mechanism themselves.

3. PARAMETER SETTING AND EXPERIMENTAL DESIGN

The problem of choosing optimal or 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. For this, statistical methods like Design of Experiments (DOE) as well as tree based methods (classification and regression trees (CART)) are used to set up computer experiments in an efficient manner.

We demonstrate our technique on six test functions – the Kursawe, Quagliarella, $ZDT-1$, Schaffer, Multi-Sphere and the single objective Sphere model.

4. EVALUATION

The applicability of the predator-prey model is demonstrated in this section. In Section 1 one of the main advantages of predator-prey models is named by "scalability". This advantage has to be shown in an experimental manner at first. The Sphere model is chosen for this task. Next the model is applied to the convex test functions. Two important questions are analyzed: the impact of the number of demes used in the model and the influence of a variable number of predators per objective. The results of the model for the concave test functions finalize this section.

4.1 Scalability

The experiments in this section were set up in order to solve the single-objective function Sphere model. Therefore the number of predators are set to $N_{pred1} = 1$ and $N_{pred2} = 0$, respectively. The panmictic population, which is traditionally used in the evolution strategy is configured by $N_{deme} = 1$. No further modifications are necessary. The variation of three exogenous parameters will change the heuristic from multi-objective to single-objective optimization. Results show that there is no significant difference between both heuristics. In particular, the predator-prey approach outperforms the ES in small dimensions ($N = \{6, 10, 20\}$). It can be conjectured that the modification of the controlling mechanism for the mutation strengths is also able to work in single objective cases.

4.2 Varying the number of demes

Here it can be seen that the number of demes has a significant impact on the number of different solutions in the resulting population. Starting from a panmictic ($N_{deme} = 1$) model only few solutions covering a very small region of the Pareto-front are obtained. Already the use of two separated demes allows to cover the whole region but with poor diversity. If the number of demes increased the final population gets more and more diverse. Similar results can be observed from all other test functions. In general, one can state that in this model, as well as in the models with a spatial population structure, the exchange from a panmictic population structure with panmictic variation and selection operators to local ones is favorable for a better diversity of the resulting population.

Next the number of predators per objective is analyzed. As a surprising result the number of predators for each objective seems to have no significant impact for the distribution of the population. It could be conjectured that the decision if a deme is encountered by only one or both types of predators is sufficient to get a well distributed Pareto-front. Summarizing one can state that the model is able to solve multi-objective optimization problems, which have in general convex Pareto-fronts.

4.3 Non-Convex Pareto-Fronts

In a last step more complex functions (Kursawe, Quagliarella) are analyzed. While the results of the Kursawe function are encouraging, here, the control mechanism of the mutation strength leads to a well approximated Pareto-set with a relative small number of dominated solutions. The same controlling mechanism works even well on the concave function. A limitation occurs at the borders of the Pareto-front. Here, further reasons for this behavior must be detected, especially in the field of finding the optimal parameterization for this heuristic-problem combination.

5. SUMMARY

In this study the problem of adapting an evolution strategy into the field of multi-objective optimization is treated. The modified ES adapted ideas of predator-prey models from ecology. In particular, this predator-prey approach enables the practitioner to change between single-objective optimization and multi-objective optimization in an easy manner. Questions about an appropriate controlling mechanism for the mutation strength in the case of multi-objective optimization are answered via a simple but efficient modification of the hitherto fix lower bound for the mutation strength. Experiments carried out with five test functions have shown that the predator-prey model is able to produce a good set of diverse solutions along the Pareto-front for convex as well as for non-convex test functions. Even in the case of single-objective optimization, the modified controlling mechanism still allows self-adaptation with equal and sometimes better rates of convergence. The hypothesis that structured populations preserve diversity in the set of non-dominated solutions can be confirmed. It might be speculated that an approximately optimal specification of the lower bound of the mutations strengths still remains to be done.