Integrating Niching into the Predator-Prey Model using Epsilon-Constraints

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ABSTRACT

The Predator Prey Model (PPM) for multi-objective evolutionary optimization features a simple abstraction from natural species interplay: predators represent different objectives and collectively hunt for prey solutions which have to adapt to all predators in order to survive. In this work, we start from previous insights to motivate significant changes in predators by enabling adaptation of selection behavior. For this, we integrate aspects of the ϵ-Constraint method into the PPM mechanisms. Our results show that this model extension results in good Pareto-fronts for bi-objective test problems.

Categories and Subject Descriptors

I.2.8 [**Artificial Intelligence**]: Problem Solving, Control Methods, and Search—*Heuristic Methods*

General Terms

Algorithms, Experimentation

Keywords

Predator-Prey-Model, Evolutionary Multi-Objective Optimization, ϵ-Constraint Method

1. INTRODUCTION

Multi-objective optimization (MOO) has become a central topic within the broad field of evolutionary computation. There, in contrast to single objective optimization, contradicting objectives usually lead to a natural limit for improvement which is represented by a set of incomparable optimal solutions. At this limit, a solution can only be improved regarding one objective, if one or more other objectives are deteriorated. These solutions are called Pareto-optimal and can be regarded as set of optimal compromises. The set of corresponding function vectors is called Pareto-front.

Although evolutionary algorithms [1] are long established solution strategies for single-objective problems, a transfer of these concepts to multi-objective problems started only in the late 1980th. While the single-objective case allows a straightforward application of the standard evolutionary loop, the evolutionary selection process is more difficult to realize for multi-objective problems as solutions can be incomparable. Nevertheless, most modern approaches follow the evolutionary loop principle and incorporate rather complex selection mechanisms to solve artificial and real world test problems. Most successful approaches (e.g. NSGA-II, SPEA2, PEAS) use the Pareto-dominance relation complemented by niching or diversity preservation techniques and archiving to select efficient solutions during evolution [2]. In contrast, indicator-based methods (like SMS-EMOA or IBEA) aggregate solutions' qualities into a single value which is then used for comparison.

For most approaches, the main research lies in the selection procedure which shifts the focus of algorithm research from considering new algorithmic principles to the design of better selection mechanisms. In fact, currently more effort is put into fine-tuning the selection mechanisms of such established algorithms than to investigate alternative algorithmic principles. Therefore, we return to the PPM [5] for MOO which consists of spatially distributed solutions represented as prey. Further, it involves chasing predators—actually realized as independently acting agents—which represent the different objectives. While roaming throughout the spatial population predators collectively influence the preys' evolution. Specifically, only local selection is performed regarding a single objective in a restricted neighborhood. This simplifies the selection process and brings inherent parallelization potential. On the long run, it is expected that prey adapt to all predator influences such that they eventually cover all optimal trade-offs.

However, the expected, almost magical emergence of predator influence towards a good solution set is often too optimistic: due to the single-objective selection, prey primarily tend to reach particularly extremal solutions. Thus, non-convex problems are rather hard to handle with this concept. Previous work, however, has demonstrated the benefits of the PPM's modular design [3] and provided a foundation [4] for the extension with ϵ-Constraints proposed in this paper.

2. THE EPSILON-PPM ALGORITHM

In order to tackle the problem of strong extremal tendency, we represent predators as different species and allow them to adapt their single-objective search mechanism by integrating ϵ-Constraints as niching strategy and predator cooperation for exploration of the whole search space in order to determine adequate ϵ-bounds. As much as a predator in the PPM, the ϵ-Constraint method focuses mainly on a single objective. One of the objectives is considered to be op-

GECCO'11, July 12–16, 2011, Dublin, Ireland.
ACM 978-1-4503-0690-4/11/07.

timized while all remaining objectives are transformed into constraints by defining an upper bound for each of them.

2.1 Algorithmic Concept and Implementation

The predator moves throughout the spatial population and selects the worst prey from its very local neighborhood regarding one objective f_c of problem F. Further, it considers the bounds $\beta = \{\beta_i | \beta_i \in \mathbb{R}, i = 1, \dots, m\}$, m number of objectives, with $\beta_c = \infty$ and finally applies selection as well as reproduction applying a genetic operator to prey in the predator's direct neighborhood. After breeding and evaluating the offspring, the worst prey is removed, if it is dominated by the offspring. Each predator applies this procedure independently—respecting its specific objective and bounds—to the prey population. The right hand side of Figure 1 shows the expected effect of predators' actions when we consider two predators which select regarding objective f_1. Due to the single objective selection, f_1 is minimized until the upper ϵ-bound for objective f_2 is reached. Locality of selection and penalization of bound violations lead to the known extremal behavior. Multiple bounds result in a certain niching behavior which generates different intermediate trade-offs along the Pareto-front.

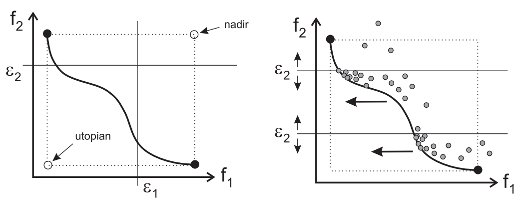

Figure 1: Schematic depiction of ϵ-PPM extension.

2.2 Niching and Detection of the Feasible Area

Using the ϵ-Constraint method implicitly assumes a range for possible bound values which depends on the considered objective and thus on the whole problem. The *utopia* and the *nadir* vector can be used in function space to define the feasible area. In our approach, the predators cooperate to determine the utopia point: If two predators with the same objective meet on the spatial structure they exchange information of their currently best discovered objective value and adopt it for further propagation to other predators. The nadir information is generated downstream when the current utopian value remains almost unchanged and is also propagated between predators. Note, nadir information is always discarded when utopian values improve significantly. Exemplary, the feasible area is shown on the left hand side of Figure 1 together with utopia and nadir point. Using the information about the detected feasible area, each predator's individual search bound is randomly changed in order to induce a niching behavior. Specifically, a small normal distributed perturbation is added to the current bound leading to a moderate change of the predators' selection pressure but still allowing the prey population to react rapidly to the new situation.

3. EVALUATION

In order to evaluate the ϵ-PPM approach, we apply it to three standard bi-objective test problems of various difficulty, namely Kursawe (KUR), and ZDT 2,3. All problems pose different degrees of complexity as well as convex and non-convex Pareto-fronts [2]. We use a 10×10 toroidal grid populated with 100 randomly initialized prey and construct two predator species with objectives f_1, f_2, and standard mutation ($\sigma = 0.05$) respectively. Finally, we bring two predators of each species to the population. An experiment terminates after overall 50.000 function evaluations and is executed 30 times each to compute Inverted Generational Distance (IGD) as well as the Hypervolume Ratio (HR) [2]. As reference vectors we use $\vec{r}_{KUR} = (10, 30)$, and $\vec{r}_{ZDT} = (12, 12)$. To judge on ϵ-PPM's performance, we apply NSGA-II and the standard PPM to the same problems.

4. RESULTS AND CONCLUSION

The evaluation of the ϵ-PPM shows that the introduced extensions contribute to both finding the feasible area and converging to the Pareto-front. Table 1 summarizes the results. We show that the integrated ϵ-Constraint approach successfully supports the algorithm in determining non-convex parts of the Pareto-front. While the original PPM covers only 81 % of the true hypervolume, ϵ-PPM almost completely covers the true front. This implicitly proofs that the active predator cooperation principle works. Obviously, the already the very simple update procedure for predator bounds produces a reliable niching behavior. Compared to the original PPM without diversity preservation mechanism, ϵ-PPM provides an important step to increase the model's performance.

Table 1: Numerical results for ϵ-PPM on the considered test problems.

Problem	Method	HR	IGD
KUR	PPM	0.9873 ± 7.4e-4	1.4e-4 ± 6.6e-6
	ϵ-PPM	0.9979 ± 3.8e-4	1.7e-4 ± 3.9e-5
	NSGA-II	0.9916 ± 3.4e-4	1.1e-4 ± 6.4e-6
ZDT2	PPM	0.1082 ± 0.0078	0.0288 ± 0.003
	ϵ-PPM	0.9978 ± 6.1e-4	0.0013 ± 4.8e-4
	NSGA-II	1.0000 ± 2.3e-6	1.9e-4 ± 8.6e-6
ZDT3	PPM	0.8145 ± 0.018	0.0254 ± 0.003
	ϵ-PPM	0.9922 ± 0.002	0.0013 ± 2.8e-4
	NSGA-II	0.9983 ± 0.006	2.9e-4 ± 6.1e-4

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