

Resource Sharing Mechanism in Co-Evolutionary Multi-Agent System

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Abstract

Evolutionary algorithms often suffer from premature loss of population diversity. This limits their adaptive capacities in dynamic environments and makes difficult the application of evolutionary algorithms to multi-modal optimization problems. Such techniques as niching or co-evolution are aimed at maintaining population diversity, species formation and the realization of open-ended evolution. This paper introduces the co-evolutionary multi-agent system with speciation resulting from co-evolutionary interactions and competition for limited resources. Such system is applied to multi-modal function optimization. The comparison with classical niching techniques is presented and the influence of resource sharing mechanism parameter's values on the course of speciation process is investigated.

1 Introduction

Evolutionary Algorithms (EAs) have demonstrated in practice efficiency and robustness as global optimization techniques. However, they often suffer from premature loss of population diversity what results in premature convergence and may lead to locating local optima instead of a global one. What is more, in the case of multi-modal optimization problems EA (without any special mechanisms) will inevitably locate a single solution [12]. If the goal is to find multiple solutions of the given problem some multi-modal optimization techniques should be used.

Niching and speciation techniques for EAs are aimed at forming and stably maintaining niches (species) throughout the search process, thereby allowing to locate the basins of attraction of local minima [13, 5] (through the rest of this paper the minimization problems are considered). During the years of research various mechanisms and techniques have been proposed. All these techniques allow niche formation via the modification of the parent selection mechanism (*fitness sharing* [8] or *sexual selection* [16]), the modification of mechanism of selecting individuals for new generation (*crowding* [11]) or the restriction of application of the selection and/or recombination mechanisms (by *grouping* individuals [10] or by introducing the environment with some topography in which the individuals are located [17]).

In EAs the fitness of each individual depends only on how well it solves the given problem. In *co-evolutionary algorithms* the fitness of each individual depends not only on the quality of solution to the given problem but also (or solely) on other individuals'

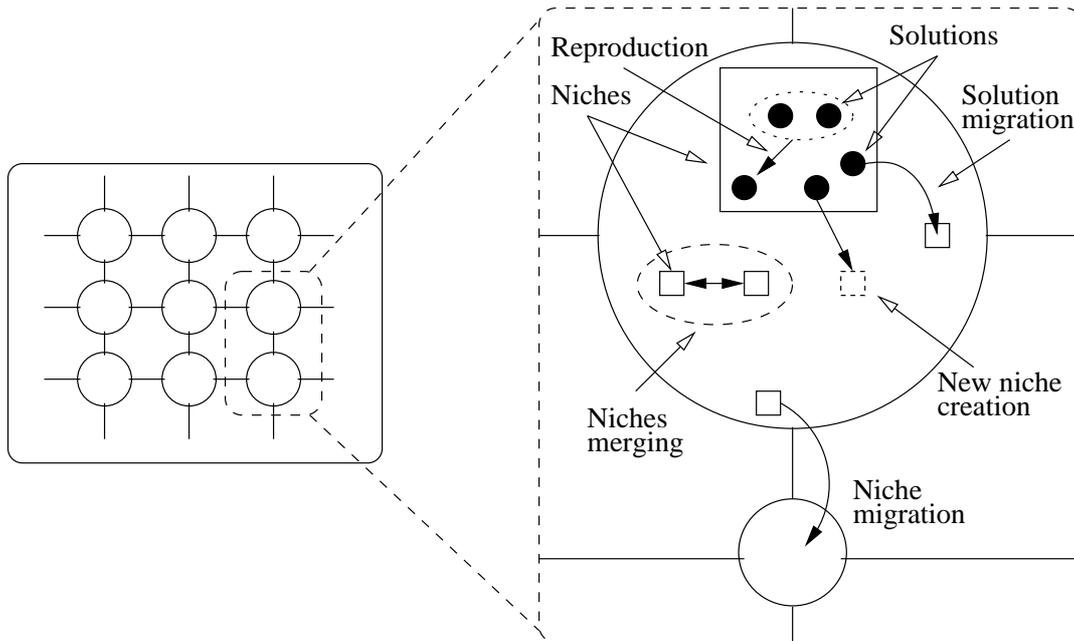


Figure 1: *NCoEMAS* system

fitness. This makes such techniques applicable in the cases where the fitness function formulation is difficult (or even impossible). As the result of ongoing research quite many co-evolutionary techniques have been proposed. Generally, each of these techniques belongs to one of two classes: competitive ([14]) or cooperative ([15]).

Although co-evolutionary techniques are aimed at overcoming limited adaptive capacities of evolutionary algorithms resulting from the loss of useful population diversity, they are not very often applied in the field of multi-modal optimization. In fact, to our best knowledge, only one niching technique based on co-evolution was developed ([9]).

2 Co-Evolutionary Multi-Agent System with Speciation

The main idea of *evolutionary multi-agent system (EMAS)* is the modeling of evolution process in *multi-agent system (MAS)* [4]. The basic EMAS model allows the evolution of only one species. The model of *co-evolutionary multi-agent system (CoEMAS)* allows modeling of biological speciation mechanisms based on co-evolutionary interactions, competition for limited resources, and geographical isolation [6]. Systems based on CoEMAS model can be applied, for example, to multi-modal function optimization [7] and multi-objective optimization.

In figure 1 co-evolutionary multi-agent system for multi-modal function optimization (*NCoEMAS*) is presented. The topography of environment, in which agents live, is graph with every node (place) connected with its four neighbors. Within the environment two co-evolving species (niches (*nch*) and solutions (*sol*)) live. There exist resource in the environment which is given to the niches and then distributed between solutions, that live within each niche. There is closed circulation of resource within the system. The resource can be possessed by environment or agents. Environment gives the resource to

agents and every agent’s action (such as migration or reproduction) costs some resource, so the resource is returned to the environment.

The competition for limited resources mechanism (*resource sharing* mechanism) works as follows. Each time step agent-niche a performs the $\langle get \rangle$ action. This action is aimed at gaining some resource from the environment (precisely speaking, from the node v in which agent a is located):

$$\begin{aligned} get : \quad r^a &\mapsto r^a + r_{eq} + r_{prop} \\ r^v &\mapsto r^v - r_{eq} - r_{prop} \end{aligned} \quad (1)$$

where r^a is the amount of resource that is in the possession of agent a , r^v is the amount of resource that is in the possession of node v , r_{eq} is the amount of resource given to each agent-niche, and r_{prop} is the amount of resource that is proportional to agent-niche fitness value. The minimal amount of resource (r_{eq}) is given to each agent-niche in order to keep alive less fitted species of agents-solutions.

Next each agent-niche distributes its resource among agents-solutions that currently belong to it. The resource is distributed proportionally to agents-solutions’ fitness values with the assumption that each agent-solution can possess no more than r_{max}^{sol} of resource.

Niches can migrate within the environment and all solutions live within niches and migrate with them within the environment. Each time step every solution searches for the niche that is located within the basin of attraction of the same local minima. Modified version of hill-valley function ([18]) is used in order to check if two individuals are located within the basin of attraction of the same local minima. If there are no niches located in the same basin of attraction, agent-solution creates new agent-niche, which genotype is the copy of its own genotype (niche is splitted into two niches).

Then each agent-solution searches its niche for the reproduction partner. Reproduction takes place only when agents have enough amount of resource. The genotypes of all agents are real-valued vectors. Intermediate recombination [3] and mutation with self-adaptation [2] are used for solutions and special mutation for niches. Each time step the agent-niche’s genotype is mutated in such a way, that the resulting genotype is the center of gravity of agents-solutions that belong to the agent-niche (fitness value of each agent-solution serves here as a weight value). Such mechanism causes that value of agent-niche’s fitness depends on the fitness values of agents-solutions that currently belong to it. Niches can merge if they are located at the same place of environment and if they are located within the basin of attraction of the same local minima.

3 The results of experiments

3.1 Test Function

In all experiments Rastrigin function was used as the test fitness landscape (see fig. 2). This is multi-modal function commonly used in studies of niching methods. Rastrigin function used in experiments is given by

$$10 * n + \sum_{i=1}^n (x_i^2 - 10 * \cos(2 * \pi * x_i)) \quad x_i \in [-2.5, 2.5] \text{ for } i = 1, \dots, n \quad (2)$$

where n is the number of dimensions ($n = 2$ in all experiments). The function has 25 local minima for $x_1, x_2 \in [-2.5, 2.5]$.

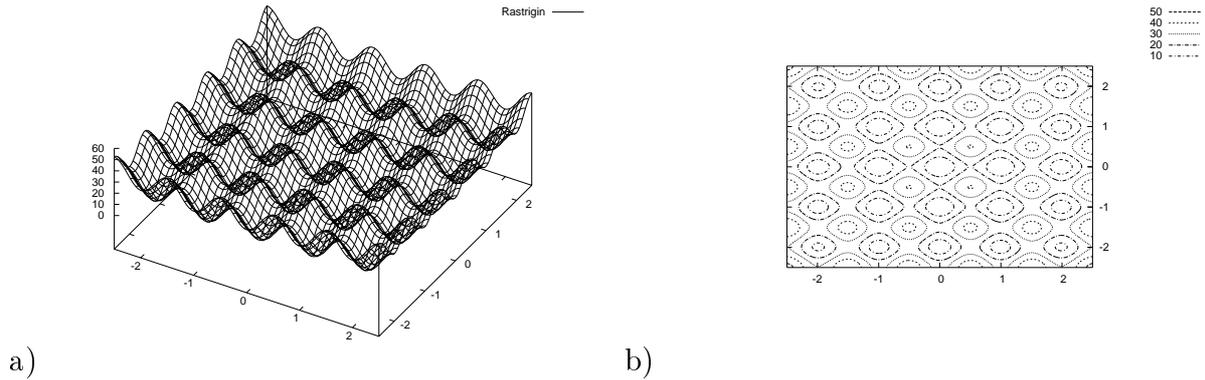


Figure 2: Rastrigin function (a) and its contour plot (b)

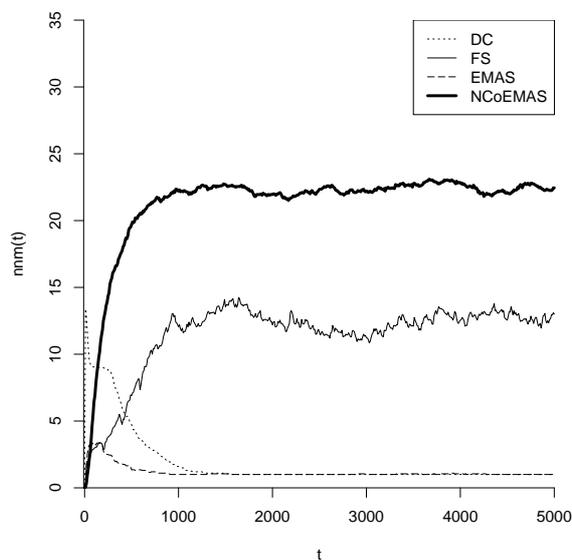


Figure 3: The number of local minima neighborhoods located (the average values from 20 experiments, $ni_{min} = 3$). The comparison of different systems' results

3.2 The Comparison of *NCoEMAS* and Classical Niching Techniques

In this section the comparison of *NCoEMAS* to other niching techniques (fitness sharing — *FS* [8] and deterministic crowding — *DC* [11]) is presented.

Figure 3 shows the average number of local minima neighborhoods located by compared systems. The local minima neighborhood was classified as “located” when there was at least $ni_{min} = 3$ individuals closer than 0.05 to that local minima. The experiments was made for four techniques: *NCoEMAS*, *EMAS*, *DC* and *FS*.

NCoEMAS stood relatively well when compared to other techniques. On the average, it stably maintained over 20 local minima neighborhoods. *DC* quickly located about 13–14 local minima neighborhoods but there was quite strong tendency to lose almost all of them during the rest part of simulation. *FS* technique detected and stably maintained about 12–13 local minima neighborhoods on the average. *EMAS* without any niching mechanism was not able to stably populate more than one local minima neighborhood.

| Parameter | $E1$ | $E2$ | $E3$ | $E4$ | $E5$ | $E6$ |
|-----------|------------------|------|--------------------|---------------------|-------------------|---------------------|
| r_{eq} | $5r_{max}^{sol}$ | 0 | $2.5r_{max}^{sol}$ | $3.75r_{max}^{sol}$ | $15r_{max}^{sol}$ | $27.5r_{max}^{sol}$ |

Table 1: The values of r_{eq} parameter for different experiments, r_{max}^{sol} is the maximal amount of resource that can be in the possession of agent-solution

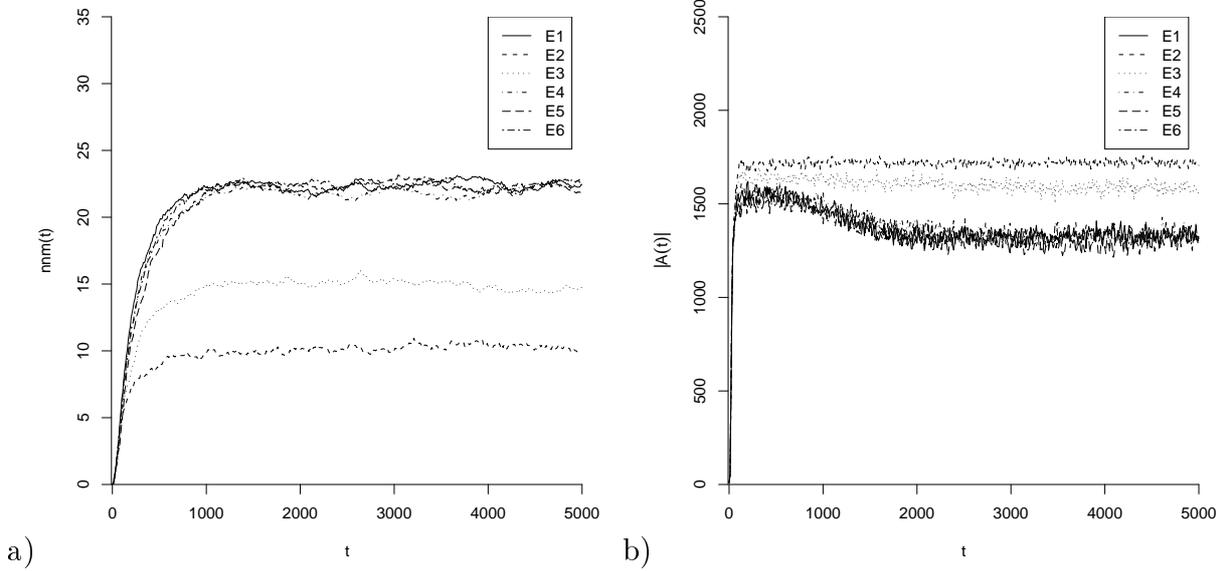


Figure 4: The number of local minima neighborhoods located (a) and the population sizes in experiments with different values of r_{eq} parameter of *NCoEMAS* system (the average values from 20 experiments, $n_{i_{min}} = 3$)

It turned out that in case of multi-modal optimization problems it works just like simple EA.

3.3 The Results of the Experiments with Resource Sharing Mechanism

In this section the results of the experiments with different values of r_{eq} parameter are presented. The value of this parameter is crucial to the correct working of the resource sharing mechanism in *NCoEMAS* system. The table 1 shows the values of r_{eq} parameter used in different types of experiments.

Figure 4a shows the number of local minima neighborhoods located in experiments with different values of r_{eq} parameter. The results are worst in the case of $E2$ and $E3$ experiments. In the case of other experiments the results are quite comparable. This means that if there are no minimal amount of resource given to the agents-niches (experiments of type $E2$) or this amount is too small (experiments of type $E3$) the species located within the basins of attraction of “worse” (that means with greater value of fitness function) local minima have no chances to survive and to win the competition for limited resources with the species located within the basins of attraction of “better” local minima.

In the case of $E2$ and $E3$ experiments the population sizes are generally larger than in the case of other experiments (see fig. 4b). The number of agents rapidly grows at the beginning of simulation, approaches some level and then stays approximately the same

during the rest of the experiment. There is no adaptation of the population size to the difficultness of the problem (to the number of local minima of the fitness function in the case of presented experiments). In the case of *E2* and *E3* experiments species located within the basins of attraction of “worse” local minima quickly loose the competition with other species and die off. In such case the operator of merging niches does not work, simply because there are no niches to merge. The number of agents stays generally at the higher level than in the case of other experiments, because the same amount of resource is given by environment to the smaller number of agents-niches and the subpopulations of agents-solutions that belong to them are bigger. In the case of other types of experiments, when there is enough resource given to each agent-niche, the number of agents in the system adapts to the number of local minima of fitness function (see fig. 4b). In such case species of agents-solutions (which live within the agents-niches) do not die off. All species has the chances to survive. The mechanism of merging niches located within the basins of attraction of the same local minima causes that after the rapid grow of the number of agents, the population size decreases slightly and approaches the optimal level.

4 Concluding Remarks

The idea of *co-evolutionary multi-agent system (CoEMAS)* allows us to model many ecological co-evolutionary interactions between species such as resource competition, predator-prey and host-parasite co-evolution, sexual preferences, etc.

In this paper sample CoEMAS with two co-evolving species: niches and solutions was presented. This system was applied to multi-modal function optimization. The presented results show that *NCoEMAS* was able to detect and stably maintain more neighborhoods of Rastrigin function local minima than two classical niching techniques and *EMAS* system.

The presented results also indicate that it is necessary to loosen the competition for limited resources between species located within the basins of attraction of local minima of different “quality”. In the case of strong competition, the species located within the basins of attraction of “worse” local minima can eventually completely die off. What is more, in such case there is no adaptation of the population size to the difficulty of the problem being solved (to the number of local minima in the case of function minimization problems).

Future research will include more detailed comparison to other niching techniques, CoEMAS based on the mechanisms of predator-prey or host-parasite co-evolution. Also the parallel implementation of CoEMAS using MPI is included in future research plans.

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