A Model of Co-Evolution in Multi-Agent System

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Abstract. Co-evolutionary techniques are aimed at overcoming limited adaptive capacity of evolutionary algorithms resulting from the loss of useful diversity of population. In this paper the idea of *co-evolutionary multi-agent system* (CoEMAS) is introduced. In such a system two or more species of agents co-evolve in order to solve given problem. Also, the formal model of CoEMAS and the results from runs of CoEMAS applied to multi-modal function optimization are presented.

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, both the experiments and analysis show that for multi-modal problem landscapes a simple EA will inevitably locate a single solution [10]. If we are interested in finding multiple solutions of comparable fitness then a multi-modal function optimization technique (*niching method*) should be used [10]. The loss of diversity also limits the adaptive capacities of EAs in dynamic environments. Co-evolutionary techniques are aimed at improving adaptive capacities and introducing open-ended evolution into EAs [11, 12].

This paper introduces the idea of *co-evolutionary multi-agent system (CoEMAS)*, which opens new possibilities of modeling different ecological interactions between species such as competition for limited resources, predator-prey and host-parasite co-evolution, sexual preferences, and so on. Also the formal model of CoEMAS and preliminary results from runs of niching co-evolutionary multi-agent system (NCoEMAS) against commonly used test functions are presented.

2 Previous Research in Co-Evolutionary Algorithms

In classical EAs each individual in the population is considered to be a potential solution of the problem being solved. The fitness of each individual depends only on how well it solves the problem. Selection pressure causes that better fit individuals have the greater chance to survive and/or reproduce and the less fit ones have the smaller chance.

In co-evolutionary systems the fitness of each individual depends not only on the quality of solution to the given problem but also on other individuals' fitness. As the result of ongoing research many co-evolutionary techniques have been proposed. Generally, each of these techniques belongs to one of two classes: "Competitive Fitness Functions" (CFF) or multi-population [11]. Also some of the niching techniques may be considered as co-evolutionary.

In CFF based systems two (or more) individuals compete in a game and their "Competitive Fitness Functions" are calculated based on their relative performance in that game [1, 4]. Each time step given individual competes with different opponents, so its fitness value varies. Because in such systems an individual's fitness depends on other individuals' fitness, they are co-evolutionary in nature.

The second group consists of systems that use multiple populations. In such systems a problem is decomposed into sub-problems and each of them is then solved by different EA [14, 13]. Each individual is evaluated within a group of randomly chosen individuals coming from different sub-populations. Its fitness value depends on how well the group solved the problem and on how well the individual assisted in the solution.

Some of the niching techniques may also be considered as being co-evolutionary since fitness of each individual depends on other individuals in a population. In fitness sharing techniques [5] each individual is considered to be the member of a niche with radius σ_{sh}. Fitness of each individual is reduced for every other individual, which lives in its niche, in a proportion to their similarity. In *co-evolutionary shared niching (CSN)* technique [6] (inspired by the economic model of *monopolistic competition*) two co-evolving populations are used. The customer population is the usual population of candidate solutions. The businessman population evolve to obtain largest payoff (best cover the peaks in multi-modal domain).

Haynes and Sen [7, 8] used co-evolution and genetic programming (GP) to design behavioral strategies of agents acting in predator-prey domain. Yong and Miikkulainen [15] studied cooperative co-evolution of agents controlled by neural networks (NNs). Although all these works also deal with the co-evolution in multi-agent systems there are some differences with our model. First, all techniques mentioned above utilize classical centralized EAs to evolve strategies or NNs, which are then evaluated in multi-agent predator-prey domain, while we are focusing on modeling of co-evolution process in multi-agent system. Second, their goal is to evolutionary design control mechanisms of agents while our CoEMAS is used as computational technique.

In [11] Morrison and Oppacher presented a general model of co-evolution for genetic algorithms. Their model can express all types of co-evolutionary relations studied in the ecological literature. However, it can not be easily applied to co-evolutionary multi-agent systems. Our approach differs to their in two points. First, we will focus on co-evolutionary relations between species rather than between individuals. The second difference results from decentralized nature of

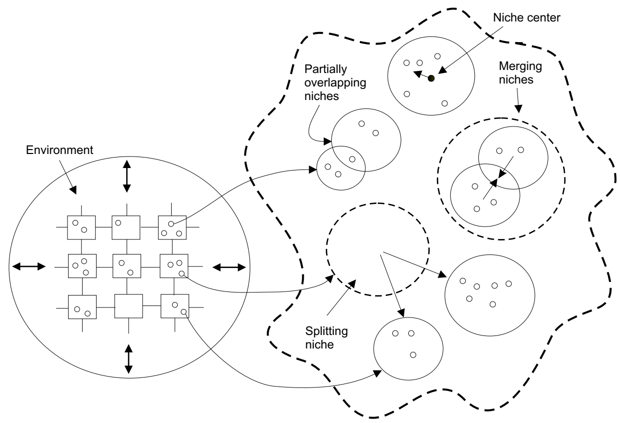

Fig. 1. Sample niching co-evolutionary multi-agent system

CoEMAS what implies different selection mechanisms and more complicated individuals that should be modeled.

In the following sections we will present the idea of co-evolution realized in multi-agent system and the formal model, which allows us to define many co-evolutionary interactions that exist in nature.

3 The Idea of Co-Evolutionary Multi-Agent Systems

The main idea of *evolutionary multi-agent system (EMAS)* is the modeling of evolution process in multi-agent system (MAS) [3]. *Co-evolutionary multi-agent system (CoEMAS)* allows co-evolution of several species of agents. CoEMAS can be applied, for example, to multi-objective optimization and multi-modal function optimization (*niching co-evolutionary multi-agent system — NCoEMAS*).

In CoEMAS several (usually two) different species co-evolve. One of them represents solutions. The goal of the second species is to cooperate (or compete) with the first one in order to force the population of solutions to locate Pareto frontier or proportionally populate and stably maintain niches in multi-modal domain.

In figure 1 sample system for multi-modal optimization with two co-evolving species: niches and solutions is presented. In such NCoEMAS we can model niches as individuals that are characterized by parameters like location, radius, etc. and evolve to best cover real niches in multi-modal domain. Two additional operators can be introduced for niches: splitting and merging. Each niche can make decision on splitting into two niches based on the current distribution of its subpopulation. Also, the decision of merging can be made by two niches that are close enough and that are located on the same peak in the multi-modal domain. In order to proportionally populate niches the mechanism of *explicit* resource sharing can be introduced. Agents' *life energy* can be treated as a resource for which individuals compete. This mechanism can be called *energy sharing*.

It seems that CoEMAS is especially suited for modeling different co-evolutionary interactions (resource competition, predator-prey and host-parasite co-evolution, sexual preferences, etc.)

4 The Model of CoEMAS

In this section the formal model of CoEMAS is presented. The model is based on the idea of M-Agent [2] and on the model of EMAS [9].

4.1 CoEMAS

The CoEMAS may be described as 3-tuple

$$CoEMAS = \langle ENV, \mathcal{S}, \mathcal{R} \rangle, \tag{1}$$

where ENV is an environment of the $CoEMAS$, $\mathcal{S}$ is a set of species that coevolve in $CoEMAS$ ($S \in \mathcal{S}$), $\mathcal{R}$ is a set of relations between species.

$$\mathcal{R} = R^{+} \cup R^{-}, \tag{2}$$

where:

$$R^{+} = \left\{ \xrightarrow{r_i +} : r_i \in RES \right\}, \tag{3}$$

$$R^{-} = \left\{ \xrightarrow{r_i -} : r_i \in RES \right\} \tag{4}$$

RES is a set of resources that exist in $CoEMAS$, $RES = \langle r_1, r_2, \ldots, r_n \rangle$.

$\xrightarrow{r-}$ and $\xrightarrow{r+}$ are relations between species:

$$\begin{aligned} \xrightarrow{r-} = \big\{ \langle S_i, S_j \rangle \in \mathcal{S} \times \mathcal{S} : & \text{ agents from species } S_i \text{ decrease fitness of agents} \\ & \text{from species } S_j \text{ via the influence on the amount of resource } r \big\} \end{aligned} \tag{5}$$

$$\begin{aligned} \xrightarrow{r+} = \big\{ \langle S_i, S_j \rangle \in \mathcal{S} \times \mathcal{S} : & \text{ agents from species } S_i \text{ increase fitness of agents} \\ & \text{from species } S_j \text{ via the influence on the amount of resource } r \big\} \end{aligned} \tag{6}$$

Having such relations defined we can easily define different co-evolutionary interactions between species that can be modeled in CoEMAS.

Definition 1 *Mutualism between two species, A and B, occurs if and only if* $\exists r_i, r_j \in RES$ *such that* $A \xrightarrow{r_i +} B$ *and* $B \xrightarrow{r_j +} A$.

Definition 2 *Commensalism between two species, A and B, occurs if and only if* $\exists r_i \in RES$ *such that* $A \xrightarrow{r_i +} B$ *and* $\forall r_j \in RES\ \neg(B \xrightarrow{r_j +} A \vee B \xrightarrow{r_j -} A)$.

Definition 3 *Predator-prey interactions between two species, A (predators) and B (preys), occurs if and only if* $\exists r_i \in RES$ *such that* $A \xrightarrow{r_i -} B$ *and* $B \xrightarrow{r_i +} A$.

Definition 4 *Competition for limited resources between two species, A and B, occurs if and only if* $\exists r_i \in RES$ *such that* $A \xrightarrow{r_i -} B$ *and* $B \xrightarrow{r_i -} A$.

4.2 Environment

The environment of CoEMAS may be described as 3-tuple

$$ENV = \langle T_{ENV}, RES, INF \rangle \tag{7}$$

where T_{ENV} is the topography of environment ENV, $RES = \langle r_1, r_2, \dots, r_n \rangle$ is a set of resources that exist in $CoEMAS$, $INF = \langle i_1, i_2, \dots, i_m \rangle$ is a set of informations that exist in $CoEMAS$.

The topography of the environment ENV is usually a graph. The distance between two nodes is defined as the length of the shortest path between these nodes.

4.3 Species

Species S that exist in $CoEMAS$ ($S \in \mathcal{S}$) can be defined as

$$S = \langle AG^S, INT^S \rangle \tag{8}$$

AG^S is a set of agents that belong to species S ($ag^S \in AG^S$). INT^S is a set of interactions with another species

$$INT^S = \langle int_1, int_2, \dots, int_n \rangle \tag{9}$$

where

$$int_i = \langle S, S_j \rangle, \quad \text{such that } S \xrightarrow{r-} S_j \vee S \xrightarrow{r+} S_j, \quad r \in RES, \quad S, S_j \in \mathcal{S} \tag{10}$$

4.4 Agent

An agent ag^S ($ag^S \in AG^S$) can be defined as 4-tuple

$$ag^S = \langle GEN, RES^S, PRF, ACT \rangle \tag{11}$$

GEN is a genotype of a given agent, for example $GEN = (gen_1, gen_2, \dots, gen_k)$, $gen_i \in \mathbb{R}$, $GEN \in \mathbb{R}^k$. RES^S is a set of resources of agent ag^S that belongs to species S ($RES^S \subseteq RES$). PRF is a set of agent's profiles with the order relation $\succ$ defined.

$$\begin{aligned} PRF &= \langle prf_1, prf_2, \dots, prf_n \rangle \\ prf_1 &\succ prf_2 \succ \dots \succ prf_n \end{aligned} \tag{12}$$

Here, profile prf_1 is the most basic profile which means that goals within this profile have precedence of another profiles' goals. ACT is a set of actions that an agent can perform.

Profile k may be the resource profile

$$prf^k = \left\{ RES^{S,k}, ST^k, RST^k, GL^k \right\} \tag{13}$$

or the information profile

$$prf^k = \left\{ MDL, ST^k, RST^k, GL^k \right\} \tag{14}$$

where

$RES^{S,k}$ is a set of resources that are used in a profile k, $RES^{S,k} \subseteq RES^S$;
MDL is a set of informations that represents agent's knowledge about the environment and other agents.
ST^k is a set of strategies that an agent may apply in a given profile, $ST^k = \langle st_1, st_2, \ldots st_l \rangle$;
RST^k is a set of strategies that are realized within profile k, $RST^k \subseteq ST^k$;
GL^k is a set of goals that an agent should realize within given profile, $GL^k = \{gl_1, gl_2, \ldots gl_p\}$.

Single strategy consists of actions taken by an agent in order to realize a goal. If agent should apply strategy that is not realized within active profile then the appropriate profile is activated.

In the case of $CoEMAS$ the set of profiles should at least include the following profiles

$$PRF = \langle prf^{res}, prf^{rep}, prf^{int}, prf^{mig} \rangle \tag{15}$$

Resource profile prf^{res} is the most basic profile and it is responsible for maintaining agent's resources above the minimal levels. Reproductive profile prf^{rep} realizes all strategies connected with reproduction process. Interaction profile prf^{int} is responsible for interactions with other individuals. The migration profile prf^{mig} is responsible for migration of given agent within the environment of CoEMAS.

5 The Application of CoEMAS to Multi-Modal Function Optimization

In this section the application of the idea of CoEMAS to multi-modal function optimization problem is presented. First simulation experiments were aimed at testing if CoEMAS is able to detect and stably maintain all peaks in multi-modal domain throughout the search process. In the following sections the system, test functions and the results of experiments are presented.

5.1 The System

The system presented in this paper is the first one, which construction is based on the idea of CoEMAS (see fig. 2). There exist two different species: niches and solutions. All agents live in 2D space, which has the structure of discrete torus. Every node of this graph-like structure has connections with its four neighbors.

All agents representing niches are located in nodes and can not change their location. Agents representing solutions are also located in nodes but they can change their location in environment migrating from node to node. Every agent-solution has some amount of resource called *life energy*. There is closed circulation of energy in the system, which means that the total energy possessed by agents and the environment is constant during the whole simulation. Agents need energy for almost every activity: migration, reproduction etc. An individual

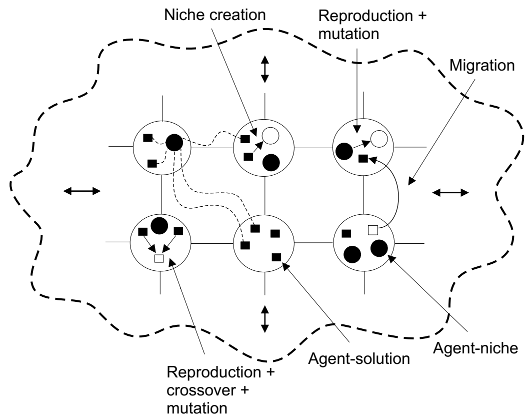

Fig. 2. NCoEMAS used in experiments

dies when its energy is equal to 0. An agent can migrate from one node to another guided by the total energy of agents living in that node. The reproduction process can take place when agent's energy is above the given level. Agent starts reproduction, searches in its neighborhood for partner and then new agent is created. Mutation and crossover (one point crossover is used) are applied with the given probability in order to produce child's chromosome. An agent created in reproduction process obtains energy from the environment.

The EA for niche population is very similar to that used for businessman population in co-evolutionary shared niching technique [6]. Each time step a single mutation site is selected randomly. The resulting individual replaces its parent if it is at least d_{min} from other niche and it is better fit than its parent. Otherwise another mutation site is selected (max. n_{limit} times).

In the time t every agent-solution searches for the closest niche (the weighted sum of Hamming distance in genotype space and Euclidean distance in environment is used). If there is no niche, such that its distance from the agent is less than given value, then the new niche is created with the copy of agent's chromosome (imprint mechanism).

In each time step less fit agents must give some amount of their energy to better fit agents (according to fitness function). Agents are compared within niches and also outside niches in the environment space. The latter comparisons are realized within nodes. Given agent is compared with agents that stay in its node and also with agents from the neighboring nodes.

5.2 Test Functions

There were four test functions used in experiments (see fig. 3 and 4): F_1, F_2, F_3, F_4 [5,10]. These functions are commonly used as baseline tests in studies of niching methods. They are a starting place for testing new niching techniques and

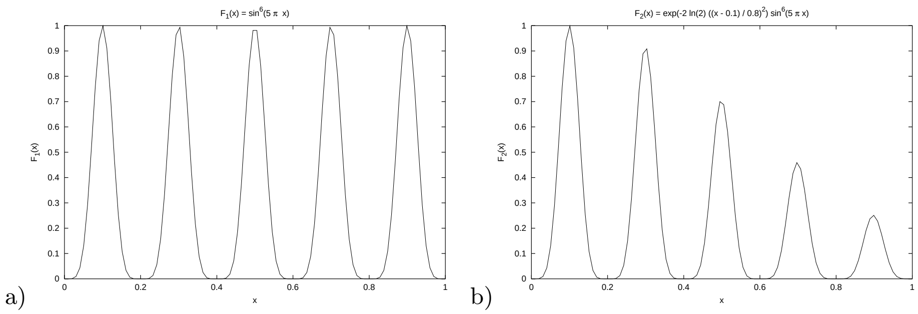

Fig. 3. Function F_1 (a) and F_2 (b)

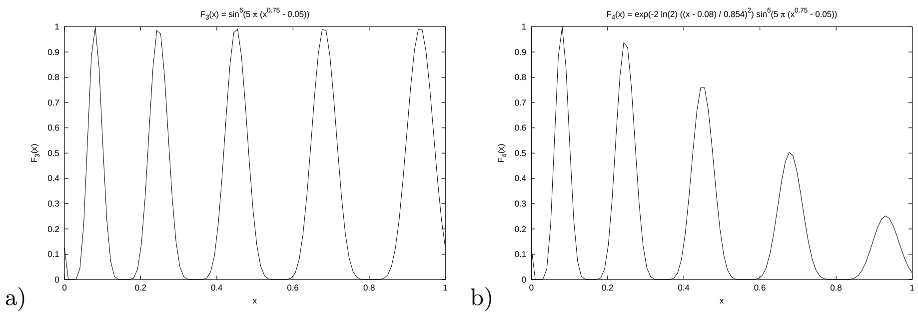

Fig. 4. Function F_3 (a) and F_4 (b)

comparing them to earlier works. Although these are very simple functions many potential nichers have in the past had problems with detecting and maintaining all of their peaks.

5.3 Results

In this section the results from runs of NCoEMAS against test functions are presented.

Figure 5 shows the average numbers of agents representing solutions within each niche from ten runs of NCoEMAS against F_1 and F_2 functions. It can be seen that NCoEMAS properly detected and stably maintained peaks of these two test functions. What is more, peaks were populated proportionally to their relative fitness.

In case of F_3 function (see fig. 6a) NCoEMAS also properly detected and stably maintained all peaks in multi-modal domain. However peaks were not properly populated. All niches should be equally populated but it seems that agents preferred wider peaks. Peaks of F_4 function (fig. 6b) were also properly located and populated almost proportionally to their relative fitness. The problems mentioned above are connected with energy sharing mechanism, what is the subject of ongoing research.

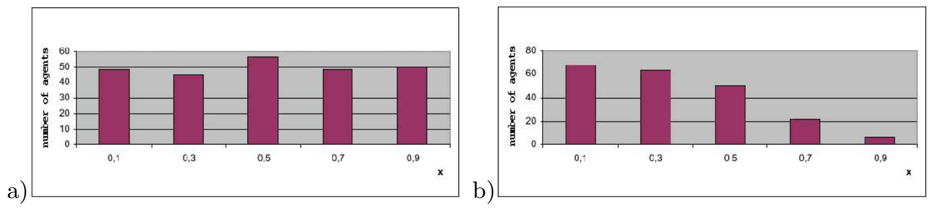

Fig. 5. The average number of agents-solutions within each niche from ten runs of NCoEMAS against function F_1 (a) and F_2 (b)

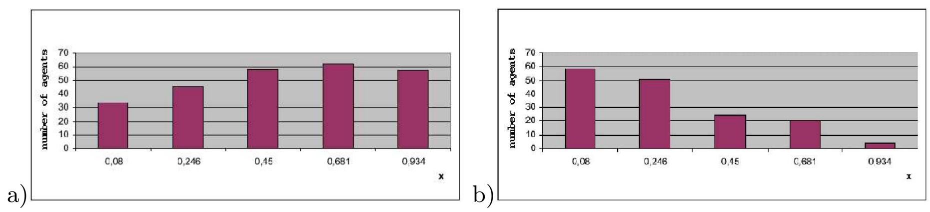

Fig. 6. The average number of agents-solutions within each niche from ten runs of NCoEMAS against function F_3 (a) and F_4 (b)

6 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 the formal model of co-evolution in multi-agent system was presented. Also, we applied this model to the construction of system for multi-modal function optimization (*niching co-evolutionary multi-agent system*).

NCoEMAS presented in this paper was based on co-evolution of two species: niches and solutions. System properly detected and maintained all peaks of test functions and, as presented preliminary results show, has proved to be the valid and promising niching technique.

Future research will include: experiments with more complex test functions, the comparison to other co-evolutionary approaches (especially to Goldberg and Wang's CSN technique), CoEMAS based on the mechanisms of predator-prey (host-parasite) co-evolution and sexual preferences, the application of CoEMAS to engineering shape design problems, and parallel CoEMAS.

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