

Classical and Agent-Based Co-Evolutionary Techniques

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Evolutionary algorithms (EAs) have demonstrated in practice efficiency and robustness as global optimization techniques. However, they often suffer from premature loss of population diversity which 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. 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 [4].

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 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 [4]. 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 [2]. Each time step given individual competes with different opponents, so its fitness value varies.

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 [5]. 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 *co-evolutionary shared niching (CSN)* technique [3] (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 the largest possible payoff (cover the peaks in multi-modal domain).

The main idea of *evolutionary multi-agent system (EMAS)* is the modeling of evolution process in multi-agent system (MAS) [1]. *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*

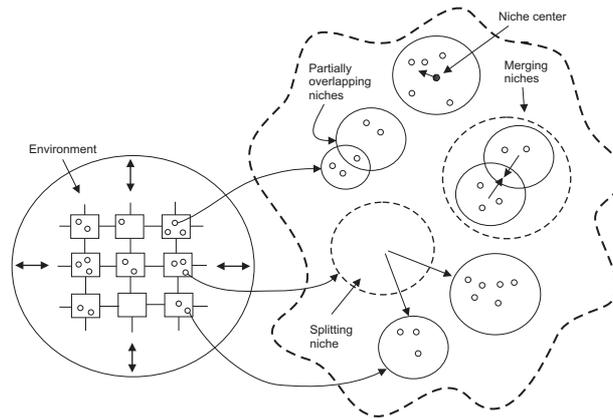


Figure 1: Sample niching co-evolutionary multi-agent system

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 a 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.

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.)

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