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A dynamic optimization approach to the design of cooperative co-evolutionary algorithms

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ABSTRACT

Cooperative co-evolutionary algorithm (CCEA) decomposes a problem into several subcomponents and optimizes them separately. This divide-and-conquer feature endows CCEAs with the capability of distributed and high-efficiency problem solving. However, traditional CCEAs trend to converge to Nash equilibrium rather than the global optimum due to information loss accompanied with problem decomposition. Moreover, the interactive nature makes the subcomponents' landscapes dynamic, which increases the challenge to conduct global optimization. To address these problems, a multi-population mechanism based CCEA (mCCEA) was proposed to compensate information in dynamic landscapes. The mCCEA is decentralized for each subcomponent since it doesn't need centralized archive or information sharing. It focuses on both the global and the local optima of each subcomponent by maintaining multiple populations and conducting local search in dynamic landscapes. These optima are seen as the current representatives of the subcomponents and used by the other subcomponents to construct their complete solutions for fitness evaluation. Experimental study was conducted based on a wide range of benchmark functions. The performance of the proposed algorithm was compared with several peer algorithms from the literature. The experimental results show effectiveness and advantage of the proposed algorithm.

1. Introductions

Cooperative co-evolution is primarily a biological concept, but has been applied to many other fields by analogy. In the field of evolutionary computation, Potter and De Jong [1,2] proposed cooperative co-evolutionary algorithm (CCEA) by introducing divide-and-conquer strategy to divide a problem into several subcomponents which are then evolved separately. The divide-and-conquer evolution scheme offers CCEAs the advantage of decomposing a complex optimization problem into a number of relatively simpler subproblems and solving them concurrently. This endows CCEAs with the potential of distributed computation and high problem-solving efficiency. CCEAs have been extended to fields of machine learning [3], rough set attribute reduction [4], multi-objective optimization [5],wireless sensor networks [6], cooperative planning [7] and clustering [8]. Especially in recent years, CCEAs have been applied to deal with large scale optimization based on many successful problem decomposition approaches [9–12].

However, the divide-and-conquer strategy is a double-edged sword. By decomposing a problem into subcomponents, CCEAs may lose a great deal of information. A subpopulation only represents the corresponding segments of the complete solutions. Collaborators must be collected from the other subpopulations to construct complete solutions for fitness evaluation. Obviously, the fitness of an individual is sensitively affected by the collaborators from the other components. In addition, CCEAs can be modeled with evolutionary game theory (ETG) [13]. From the theory perspective, CCEAs may gravitate towards suboptimal solutions represented by Nash equilibria rather than global optima in the complete problem. This may lead to some inherent problems. The most typical one is relative overgeneralization (RO), in which the subpopulations are likely to converge to the Nash equilibria with larger basins of attraction regardless of whether they are global optima (as illustrated in the next section).

The suboptimal convergence of simple CCEAs is essentially different from that of the common EAs, which can be addressed by maintaining proper population diversity. Effective information compensation methods should be incorporated into CCEAs to enhance global optimization. Many works have been done to design information compensation scheme for CCEAs. From the interactive

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nature of the CCEAs, information compensation could be archived from both sending and receiving perspectives.

The archive based method is an intuitive and popular way to compensate information from the sending perspective. For example, in [14,15] Nash memory is maintained to help subcomponents converge to the global optimal equilibrium. Also, the nature of diversity maintenance of Pareto dominance population [16] or reference [17] is utilized to design CCEAs for global optimization. In addition to explicitly recording information in additional archives, the co-evolutionary information can also be recorded or maintained implicitly. In [18], memory is implicitly added to a co-evolutionary computation framework by embedding the subpopulations into a spatial geometry, which can help maintain adaptive gradients to improve the global optimization performance.

As for the research from sending perspective, it has not been studied as extensively as the way to compensate from receiving perspective. Most of the work in the literature uses a *best-and-N-random* strategy (one best and N random individuals), and little work can be seen to explore what information should be exchanged among subcomponents to achieve information compensation. Panait and Luke [19,20] argued that "subpopulations should not necessarily explore only their most promising solutions, but also those solutions that provide the other subpopulations with accurate projections of the joint search space." They proposed a scheme to help one subcomponent select informative collaborators for the co-evolution of the other subcomponents. Although the experimental results are positive on the RO-featured problems, one subpopulation needs to access all individuals of the others'. Such centralized whole-population accessing will lead to large amount of communication and fitness evaluations, which is impractical especially in network based cases.

Therefore, the research into CCEAs which can globally optimize with reasonable numbers of collaborators is still in its infancy, and the need for efficient methodologies is demanded. In this paper, we design an improved CCEA under the following intuitive motivation: Local and global optima can well feature the landscapes of subcomponents, when these optima are used as representative collaborators subpopulations will be provided with more sufficient information for co-evolution.

To search those representative collaborators, the dynamic nature of the landscapes of subcomponents must be taken into account. The evaluation of an individual depends on the collaborators from the other subpopulations and these collaborators may vary through out the co-evolution process, which means that the evaluation of a certain individual is not static but dynamic. Although it has been realized in early work [13], little work deals with it. If this feature were considered when designing a CCEA, more representative information could be searched and the subpopulations could conduct co-evolution with better collaborators. Fortunately, the methodologies for enhancing EAs to search in dynamic landscapes have been intensively studied especially in the past decade (see the surveys and books [21–24]). Thanks to these improvements, co-evolution of subcomponents regarding the dynamic landscapes has become practical.

Bearing these ideas and motivations in mind, an improved CCEA is suggested, investigated, and discussed in this work. In general, the contributions of this work can be summarized as follows:

- A multi-population scheme has been proposed to dynamically discover and maintain multiple optima for a given subcomponent: several child populations can be adaptively split off from the base population (the population of a given subcomponent) or merge to track the spatial optima (local or global). The base population adopts a population based genetic algorithm to explore new optimum in the whole sub-landscape, while the child populations adopt local search to exploit discovered optima efficiently.
- A two-fold information compensation technique is introduced: The optima found by the multi-population scheme are used as information carriers and exchanged among subcomponents to achieve information compensation from the interaction sending perspective. On the other hand, historic best solutions of the child populations are maintained along with the complete solution contexts. Such solution contexts are utilized in the fitness evaluation procedure to achieve information compensation from the interaction receiving perspective. Such a two-fold information compensation mechanism enables CCEA to effectively tackle the inherent difficulty when optimizing RO-featured problems.
- The proposed multi-population scheme based CCEA framework can run without centralized information sharing or large amount of random information exchange, which make the algorithm more practical for real-world applications.

This paper is extended from our previous work [25] in which a dynamic multi-population evolutionary algorithm and a grid-based archive were integrated into CCEA to conduct information compensation. This paper extends this previous work in the following aspects. First, we modified the criterion for merging two overlapped populations; Second, we use different optimizers in different kind of populations; Third, we proposed a new method to conduct fitness evaluation using the historic information and the collaborators instead of grid-base archive method. At last, in experiments section, wider benchmark functions and more peer algorithms are involved, comparison and analysis are more exhaustive.

The remainder of this paper is organized as follows. In Section 2, the CCEA principle and the relative overgeneralization problem is demonstrated. The techniques concerning evolutionary computation in dynamic landscapes are also briefly reviewed. Section 3 is devoted to the description of the proposed algorithm. Section 4 presents the experimental results and discussions. Finally, Section 5 provides conclusions and future work.

2. Background and related work

2.1. CCEA and relative overgeneralization problem

CCEAs speed up the optimization process by decomposing a problem into subcomponents that can be concurrently optimized by several subpopulations. The main difference between classical evolutionary algorithms (EAs) and CCEAs is that in CCEAs an individual only codes a segment (according to its subcomponent) of the solution, it have to collect collaborators from the other subpopulations to construct complete solutions for fitness evaluation. In the example shown in Fig. 1, the whole problem is divided into three subcomponents and each of them is evolved by a subpopulation. As for the individual "0101" in subpopulation A, its fitness evaluation is realized by combining with collaborators from the other subpopulations ("1001" from subpopulation B and "1100" from subpopulation C). Consequently, the fitness value of "0101" is indeed the evaluation value of "0101|1001|1100" according to the global fitness function f.

It is always highly desired that a given problem should be decomposed according to the dependence relationship between the decision variables when conducting cooperative co-evolution. If any decision variable in a subcomponent only depends on the variables within the subcomponent, the algorithm can effectively converge to the global optimum by exchanging the best solutions among subcomponents. In other words, if there is no information loss after decomposition, global optimization could be guaranteed. This is because the underlying landscape of a subcomponent is not

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