CoEvolutionary Approaches in Cognitive Robotic System Design

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1 Introduction

In recent years, a large number of research efforts have been directed towards implementing cognitive robotic systems. One of the approaches for accomplishing cognitive system design is by following an optimization procedure. In particular, following this approach, the complete structure of the cognitive system is described by a set of parameters, while an optimization process is utilized to explore the parameters domain, identifying those values that give the cognitive system an appropriate behavior, according to a set of human-specified design criteria.

The characteristics and the effectiveness of the employed optimization methodology strongly influence the quality of the resulted system. Classical gradient-based optimization procedures are not very effective in approaching complex highly non-linear problems [1]. The limitations of traditional optimization techniques led to the growth of stochastic search methods. One very popular stochastic search approach is evolutionary algorithms which are capable of accomplishing near globally optimal solutions (e.g. cognitive system configurations) in highly non-linear problems. However, many difficulties arise with evolutionary approaches when large systems need to be implemented. In order for the employed design methodology to be more effective, it should be capable of addressing the structural characteristics of the particular system. Specifically for the cognitive systems, distributedness is one of the most widely assumed characteristics. Distributedness means that there is no central processor or homunculus that controls behavior but a distributed and functionally integrated network of recursive processes from which a coherent behavior emerges as a global product of the system. This property of cognitive systems should be explicitly addressed by the optimization design methodology in order to effectively design the overall system.

This is particularly the approach followed by coevolutionary algorithms which utilize separate populations to evolve partial entities of the problem [2, 3]. In order to formulate a composite problem solution, individuals within different populations have to be selected, put together and operate in parallel [4, 5]. In other words, coevolution breaks down the overall problem into smaller pieces and then solves partial problems taking also into account the dynamics of their interaction. The capability of coevolution to address the distributed nature of cognitive systems makes it very appropriate for being employed as an effective design methodology.

2 The Specialized Features of Coevolution

Coevolution involves two or more concurrently performed evolutionary processes with interactive performance. Initial ideas on modeling coevolutionary processes were formulated by [6-9]. Typically, separate populations are employed to evolve the identifiable entities of the problem[1]. Each population is able to use its own

[1] Initially, works using single population models were also referred as coevolutionary approaches (e.g. [10]). However, here we concentrate only on the schemes employing two or more distinct populations, because this approach is followed by the majority of recent works [11].

evolutionary parameters (e.g. encoding, genetic operators), providing increased search competencies to the overall optimization procedure [4, 12]. This is due to the utilization of partial populations which on the one hand decomposes the overall problem domain in smaller and more easily searchable areas, and on the other hand provides the opportunity to the designer to address effectively the particular features of each entity in the problem.

The design of a fitness function is a very crucial factor for the successful convergence of evolutionary processes. Coevolution differs from ordinary evolutionary algorithms in terms of fitness function usage, because the evaluation process is based on interactions between individuals. Each individual represents a distinct component of the problem which has to interact with the others in order to construct an effective composite solution. In other words, the fitness function is non-stationary, but it is also based on the quality of co-existing individuals representing other entities of the problem [13]. Since the fitness measure is specified relatively to other individuals, each improvement on one partial population is triggering further improvements in other populations. Additionally, it is worth emphasizing that the plasticity of the fitness measure has the advantageous side-effect of the effortless maintenance of diversity in partial populations. Thus, it is not surprising that several studies report that coevolution outperforms unimodal evolution [14-16].

3 Coevolutionary Approaches and Cognitive/Robotic System Design

Research efforts on cognitive robotic systems are often investigating the self-organization of decentralized structures. This is usually done either by addressing distributed control systems serving as robot brains, or by exploring how social interaction enforces the emergence of new behaviors at both an atomic and a group level. At the same time, following the discussion in the previous section, coevolutionary approaches are very good at tackling distributed problems. As a result, it seems that coevolution is well suited for the specialized needs of cognitive systems design, and it can successfully serve as a tool for research in the area.

Coevolutionary approaches are broadly distinguished into competitive and cooperative approaches [17]. In the following, we present each one of them and we discuss the type of problems they fit best. Additionally, we briefly review their previous applications to designing cognitive robotic systems.

3.1 Competitive Coevolution

Competitive coevolutionary models are especially suitable for problems that can be stated in the form of two or more opponent entities [11]. These approaches are often described in terms of co-evolving solutions and test cases, in interacting populations. In particular, each opponent utilizes the others as test cases in order to estimate its fitness quality. Following this approach, competition takes place between partial evolutionary processes, i.e. the success of the one implies the failure of the other [8, 18-20]. The fitness of a candidate solution is proportional to the number of test cases it solves, while the fitness of a test case is proportional to the candidate solutions which fail to solve it [21]. As a result, it is expected that each opponent will become increasingly more efficient by exploiting the weakness of the other, and also eliminating its own weak points.

Competitive coevolution is suitable for problems that are difficult to formulate an objective fitness function, but can be easily described by an antagonistic scenario. In the field of cognitive robotics the majority of competitive coevolutionary approaches have been employed in predator/prey -like problems [22-24]. Competing populations, representing either a predator or a prey robot, reciprocally drive one another to increasing levels of complexity by producing an evolutionary arms race, where each group becomes gradually more efficient. Competitive coevolution has been also proposed as an abstract model of cognitive operation, simulating the way humans make iterative revisions to problem specifications [25]. Furthermore, a similar antagonistic scenario has been also suggested as a tool for studying competing internal dynamics in the brain [26].

3.2 Cooperative Coevolution

The cooperative scheme provides an appropriate framework for evolving distributed systems consisting of non-linearly interacting components that need to be co-adapted on one another [2, 27]. The standard approach to applying cooperative coevolution is based on the natural decomposition of a problem into its partial components [3, 4, 28-30]. In particular, the structure of each component is assigned to a different subpopulation. Then, components are evolved simultaneously, but in isolation from one another. In order to evaluate the fitness of an individual from a given partial population, collaborators are selected from the other subpopulations, and the combined chromosome is decoded to form a complete solution of the problem which is further tested and evaluated [3]. As a result, each component achieves successful performance only by helping the other components to also perform in an efficient way. The crucial role of component interaction in cooperative coevolution, enforces the coupling of partial structures and the formulation of successful composite solutions.

Cooperative coevolution has been successfully applied in the field of robotics for implementing distributed autonomous systems. The majority of applications lie in the field of multi-agent systems, aiming at designing robots which are capable of solving complex tasks by means of developing an integrated collective functionality [31-33]. In a similar way, other works employ a set of neural agents that together compose a single artificial brain for robotic systems [34,35]. Cooperative coevolution also has been employed for implementing systems based on the well known mixture of experts approach, where each expert develops a different role specializing in a specific portion of the whole problem [36]. Furthermore, recently cooperative coevolution was employed for implementing biologically inspired brain-like computational models [35, 37], that make robots capable of solving well-known cognitive tasks.

4 Conclusions

Coevolution is a relatively new computing approach that has gained the interest of many researchers in recent years. In particular for the field of cognitive robotic systems, coevolution provides a new framework for investigating how complex cognitive phenomena emerge from the interaction of simple entities, and thus, it can be expected to significantly support research endeavors in the area.

Regarding the joint future of coevolutionary techniques and cognitive robotic systems, one can find many interesting research topics that are worth investigation. Among them, we distinguish the following two general research directions. Firstly, further work is necessary for the improvement of coevolutionary algorithms and their capability to address large and difficult problems, providing also a framework for analyzing the internal dynamics of the design procedure and the shaping/emergence of new behaviors. Secondly, new design methodologies are required that take advantage of the distributed characteristics of cognitive systems being capable to scale up in terms of both their computational structure and their behavioral repertoire, self-organizing successfully into gradually more sophisticated systems. The further development of coevolutionary approaches could provide an efficient solution to this problem.

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