Evolution Tunes Coevolution: Modelling Robot Cognition Mechanisms

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Abstract. We introduce a framework for brain modelling tasks, following a collaborative coevolutionary approach. A new coevolutionary scheme is also proposed which emphasizes collaborator selection issue. The proposed approach is employed to construct a computational model of brain motor areas, which is tested in driving a simulated robot.

1 Introduction

The problem of brain modelling fits very well to collaborative coevolutionary approaches, since the mammalian central nervous system consists of distinct interconnected modules [1]. Thus, separate coevolved species can be used to perform design decisions for each partial brain model, enforcing both a performance similar to reality and the cooperation within brain modules. However, there are open issues in the area of coevolutionary processes. One major problem concerns how collaborators are chosen among species [3]. We propose a two level collaborative coevolutionary strategy, aiming at a systematic method to approach collaborator selection. An additional evolutionary algorithm which performs in a higher level is employed to evolve collaborator schemes. In conjunction with the enhancement of single individuals performed in coevolved species, higher level evolution also performs the enhancement of successful assemblies of partial solutions.

2 Two Level Collaborative Coevolution

We implemented a general purpose genotype for both the evolution of species, and the higher-level collaborator selection process. Each individual is assigned an identification number, and encodes two kinds of variables. The first kind is SetVariables which are allowed to get a value from a unordered set. The second kind is termed RangeVariables and it is allowed to get a value within a range. Higher level evolutionary process performs on a population of individuals consisting only of SetVariables. Each SetVariable is joined with one lower level species. SetVariable's value can be any identification number of the individuals from the species it is joined with. In order to test the performance of individuals, the population at the higher level is sequentially accessed, and SetVariable's values are used as guides to select collaborators among species.

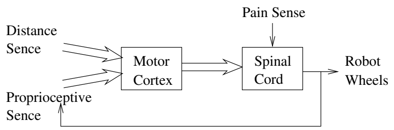
K. Deb et al. (Eds.): GECCO 2004, LNCS 3102, pp. 640–641, 2004.

Some individuals of the lower level species may be multiply selected to participate in various combinations. Unused individuals are utilised to decrease the heavy multiplicity of collaborations, by a novel genetic operator termed "Replication". For each non-collaborative individual x of a species, replication identifies the fittest individual y with more than max_c collaborations. The genome of y is then copied to x, and x is assigned $max_c - 1$ collaborations of y, by updating the appropriate individuals of the population at the higher level. After replication, individuals x and y are allowed to evolve separately.

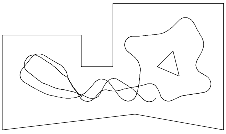
3 Results

We employ the computational model presented in [2] to supply a computational structure for brain modelling. The latter consists of a neural cortical module to represent brain areas and a link module to support information flow within them. The computational model learns in two modes. The first mode represents phylogenesis (simulated by the coevolutionary process) and the second represents epigenesis (simulated by synaptic adjustment during environmental interaction).

The connectivity of neural network structures is illustrated in Fig 1(a). The whole model consists of 5 subcomponents (2 Modules and 3 Links) which have to cooperate to accomplish the desired performance. A higher-level evolutionary process with genomes of 5 SetVariables tunes the coevolution of all 5 species following the method presented in section 3. A population of 150 individuals evolved subcomponent species, while a population of 300 individuals evolved higher-level collaborator selection process. A sample result of phylogenetic process regarding the learning of a wall avoidance behaviour is illustrated in Fig 1(b).



(a)



(b)

Fig. 1. (a) Schematic overview of the model. (b) Sample result of robot navigation.

References

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