CoEvolutionary Incremental Modelling of Robotic Cognitive Mechanisms

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Abstract. Recently, brain models attempt to support cognitive abilities of artificial organisms. Incremental approaches are often employed to support modelling process. The present work introduces a novel computational framework for incremental brain modelling, which aims at enforcing partial components re-usability. A coevolutionary agent-based approach is followed which utilizes properly formulated neural agents to represent brain areas. A collaborative coevolutionary method, with the inherent ability to design cooperative substructures, supports the implementation of partial brain models, and additionally supplies a consistent method to achieve their integration. The implemented models are embedded in a robotic platform to support its behavioral capabilities.

1 Introduction

The long-term vision of developing artificial organisms with mammal-like cognitive abilities, has recently given impetus in brain modelling studies. The brain of mammals consists of several interconnected modules with different functionalities [5], which implies that models with distributed architecture should be designed. Recently, we proposed a novel coevolutionary method [6] [8], to design distributed partial brain models. Specifically, neural network agents are coevolved by distinct species (populations) emphasizing both their autonomy and cooperability with the remaining structures.

Additionally, incremental brain modelling approaches have been proposed [9, 15, 13]. However, the computational structures employed by the proposed incremental approaches suffer in terms of scalability, and can not be used widely as a brain modelling computational framework. This is because substructures are originally designed to handle a specific amount of incoming information. Thus, by performing incremental modelling steps, the structures are difficult to operate successfully because new modules are integrated, and additional information volume is projected on them. Furthermore, no optimization method is employed to support the incremental modelling process. Neural network integration processes have been also proposed in other contexts [16], which however do not overcome the mentioned problems.

The coevolutionary method matches adequately the incremental modelling processes due to its inherent ability to integrate distributed structures. In the present work, we propose a brain modelling method focusing on the integration of partial models in gradually more complex ones. Specifically, in order to eliminate the problem of existing computational models employed by incremental processes, we utilize neural modules with internal dynamics, which self-adapt their performance as new structures are integrated on top of them. Intermediate link modules are employed which are connected on the key points of existing structures, to properly modulate their performance. Furthermore, a coevolutionary optimization method facilitates the incremental process, offering a consistent mechanism to support the reusability of substructures. The proposed approach is assessed by embedding the implemented brain model in a robotic platform, to furnish it with cognitive capabilities.

The rest of the paper is organized as follows. In the next section we formally present the proposed computational framework consisting of the agent structures employed to represent partial brain areas, and the collaborative coevolutionary scheme which is utilized to specify the computational details of brain models. Computational experiments which follow the proposed computational framework to design a partial brain model are presented in section 3. Specifically, we demonstrate the implementation of a computational model simulating posterior parietal cortex - prefrontal cortex - primary motor cortex - spinal cord interactions in a delayed response task. Finally, conclusions and suggestions for further work are drawn in the last section.

2 Computational Framework

The proposed computational framework is inspired by the biological prototype, while at the same time serves the special needs of incremental modelling. Specifically, brain areas are modelled by flexible neural network agents. Similarly to a phylogenetic process, an evolutionary approach is employed to specify the computational details for each agent [14]. Instead of using a unimodal evolutionary process, a collaborative coevolutionary method is utilized to support neural agent specification, offering enhanced search abilities of partial brain elements [11]. In the following, we present in turn the computational structures, and the coevolutionary approach.

2.1 Computational Model

We implement two different neural agents, to supply a general computational framework: (i) a cortical agent to represent brain areas, and (ii) a link agent to support information flow across cortical modules. Their structures are an extension of those presented in [8], [7].

Link Agent. The structure of link agent is appropriately designed to support connectivity among cortical modules. Using the link agent any two cortical modules can be connected, simulating the connectivity of brain areas.

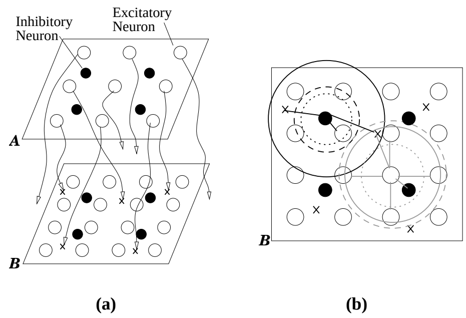

Fig. 1. Schematic representation of the computational model. Part (a) illustrates a link agent which supports information flow from cortical agent A to B. Part (b) illustrates synapse definition in cortical agent B. Neighborhood radius for i) afferent axons is illustrated by a solid line, for ii) neighboring excitatory neurons by a dashed line, and for iii) neighboring inhibitory neurons by a dotted line. Sample neighborhoods for excitatory neurons are illustrated with grey, while neighborhoods for inhibitory neurons are illustrated with black.

Each link agent is specified by the projecting axons between two cortical agents (Fig 1(a)). Its formation is based on the representation of cortical agents by planes with excitatory and inhibitory neurons (see below). Only excitatory neurons are used as outputs of the efferent cortical agent. The axons of projecting neurons are defined by their (x, y) coordinates on the receiving plane. Cortical planes have a predefined dimension and thus projecting axons are deactivated if they exceed the borders of the plane. This is illustrated graphically in Fig 1(a), where only the active projections are represented with an $\times$ on their termination. As a result, the proposed link structure facilitates the connectivity of sending and receiving cortical agents supporting their combined performance.

Cortical Agent. Each cortical agent is represented by a rectangular plane. A cortical agent consists of a predefined population of excitatory and inhibitory neurons, which all follow the Wilson-Cowan model with sigmoid activation as it is described in [8]. Both sets of neurons, are uniformly distributed, defining an excitatory and an inhibitory grid on the cortical plane. On the same plane there are also located the axon terminals from the efferent projected cortical agents.

All neurons receive input information either from i) projecting axons, or ii) excitatory neighboring neurons, or iii) inhibitory neighboring neurons. The connectivity of neurons follows the general rule of locality. Synapse formation is based on circular neighborhood measures. A separate radius for each of the three synapse types, defines the connectivity of neurons. This is illustrated graphically in Fig 1(b), which further explains the example of Fig 1(a). All excitatory neurons share common neighborhood measures. The same is also true for all inhibitory neurons.

The performance of cortical agents is adjusted by the experiences of the artificial organism, obtained through environmental interaction, similar to epigenetic[1] learning [2]. To enforce experience based subjective learning, each set of synapses is assigned a Hebbian-like learning rule defining the self-organization internal dynamics of the agent. We have implemented a pool of 10 Hebbian-like rules that can be appropriately combined to produce a wide range of functionalities. The employed learning rules are the union of those employed in [3], [6], and thus they are omitted here due to space limitation. Agents plasticity allows synaptic adjustments at run-time based on environmental experience. The most common, but harder to evolve, alternative of genetically-encoded synaptic strengths, results to a rather unmanageable problem complexity.

2.2 Collaborative Coevolution

An evolutionary process determines the self-organization dynamics of partial brain structures, enforcing the emergence of valuable behaviors during lifetime. However using a unimodal evolutionary approach, it is not possible to explore effectively partial solutions, which correspond to brain substructures. Coevolutionary algorithms have been recently proposed to facilitate exploration in problems consisting of many decomposable subcomponents (e.g [10, 11]). Distinct species (populations) are employed to estimate solutions for each partial component of the problem. Accordingly, increased search competencies are inherently available in coevolutionary algorithms, while the special characteristics of substructures can be also taken into account. Recently, we introduced the usage of collaborative coevolution for the design of partial brain models [6] [8], while in the present study we demonstrate that this approach can also serve the incremental modelling process.

Specifically, a two level collaborative coevolutionary scheme is employed. The species representing distinct elements of the composite system are evolved independently at the lower level. Additionally, an evolutionary process performs at a higher level, to select the appropriate individuals from each species that cooperatively are able to construct a good composite solution. Thus the parameter space is segmentally searched in the lower level by evolved species, while at the same time, the high level evolutionary process searches within species to identify the best collaborator schemes.

We employ two kinds of species encoding the configurations of either a Primitive agent Structure (PS) or a Coevolved agent Group (CG). PS species specify partial elements, encoding the exact structure of either cortical or link agents. A CG consists of a group of cooperating PSs with common objectives. Thus, CGs specify configurations of partial solutions by encoding individual assemblies of cortical and link agents (see Fig 2).

A general purpose genotype is employed for both the lower level evolution of species, and the higher-level collaborator selection process. According to that, each individual is assigned an identification number and encodes two different kinds of variables. The first kind is allowed to get a value from a set of unordered numbers, e.g. $\{1,5,7,2\}$, with the ordering of the elements being of no

[1] Epigenesis here, includes all learning processes during lifetime.

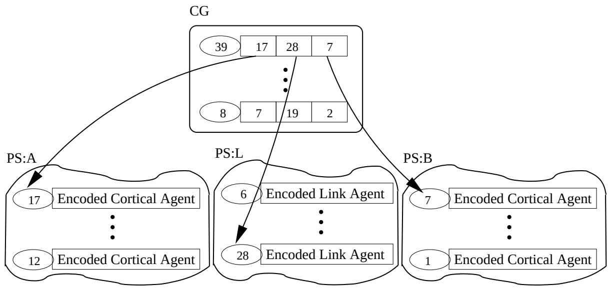

Fig. 2. A schematic overview of the coevolutionary process. CG is represented by a rounded box, while PSs are represented by a free shape. Identification numbers are represented with ovals.

use. These variables are called SetVariables. The second kind of variables is allowed to get a value within a range of values, e.g. [0,1]; therefore, they are called RangeVariables. The computational details of PS (either cortical or link) and CG structures can be easily mapped to the genotype, following a process very similar to the one described in [8]. This is omitted here due to space limitations.

In order to test the performance of individuals, the population at the higher level is accessed. The parameter values at CG-level are used as guides to select collaborators among PS species (Fig 2). The collaborators are appropriately combined to form the proposed solution which is further tested. During fitness assignment, individuals of the higher level are assigned a fitness value f, representing how good is the solution formed by the selected collaborators. Individuals of the coevolved species at the lower level are assigned the maximum of the fitness value achieved by all the solutions formed with their membership. Thus an individual of the lower level species is assigned the value $f = max\{f_i\}$ where f_i is the fitness value of the i-th solution formed with the collaboration of the individual under discussion.

Evolutionary steps are performed based on the standard evolutionary operators. First, individuals of each species are sorted according to their fitness values. Then, a predefined percentage of individuals are probabilistically crossed over. An individual selects its mate from the whole population, based on their accumulative probabilities. Finally, mutation is performed in a small percentage of the resulted population. Genetic operators are applied in both levels in the same way.

2.3 Discussion

The plasticity of agent structures, which stems from the assignment of learning rules, constitute a key feature of the proposed computational model. Specifically, it facilitates the incremental modelling process by adjusting the performance of each module to various circumstances of incoming information, enforcing the reusability of substructures. This is a novel feature of our approach since, al-

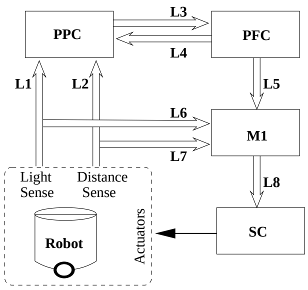

Fig. 3. A schematic overview of the Primary Motor Cortex model. Cortical agents are illustrated with blocks, while link agents are illustrated with a double arrow.

though neural structures with self-organization characteristics are widely used in many different domains, their suitability on modelling incrementally distributed systems has not been studied before.

It should be noted that coevolution is not the only methodology to approach incremental modelling. Other optimization processes (e.g. unimodal evolution) would theoretically be able to support the incremental process. However, coevolution offers many advantages in terms of searching effectively partial solutions, because it is originally designed to work with substructures instead of the composite solution. As a result coevolution matches adequately to the agent-based distributed brain modelling. This has been illustrated in [6], [8] where one-step coevolutionary processes are employed to design brain models consisting of independent but cooperable substructures with distinct functional goals.

Furthermore, the proposed coevolutionary scheme can be hierarchically organized supporting the concurrent optimization of many substructures in one-step [7]. The hierarchical approach can be used also to overcome the well known problem of incremental modelling where the constraints imposed by the structure of initial models can be too hard, harming the forthcoming incremental steps. By commencing a hierarchical coevolutionary process which loads the results of the first incremental steps it is possible to further optimize them considering also the needs of the new components. As a result "single-step" and "incremental" processes can support each other, performing in a complementary way.

3 Results

The effectiveness of the proposed approach is illustrated on the design of a partial brain computational model, which simulates posterior parietal cortex (PPC) - prefrontal cortex (PFC) - primary motor cortex (M1) - spinal cord (SC) interactions, emphasizing on working memory (WM) usage (Fig 3). We note that the proposed model does not aim to be a detailed replica of the biological prototype (e.g. premotor areas are not represented), but it serves as a guide on how incremental coevolution can be employed to support brain modelling.

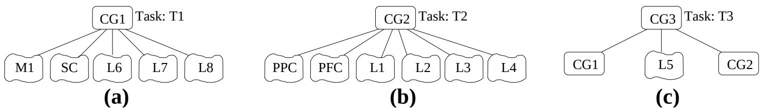

Fig. 4. A schematic overview of the incremental coevolutionary process employed to design the model of Fig 3. Part (a) illustrates the process employed to design the model of M1-SC interaction, part (b) illustrates the process designing the model of PPC-PFC interaction, and part (c) illustrates the coevolutionary process which serves their integration.

Several biological experiments highlight the behavioral organization of these brain areas. They are based on delayed response (DR) tasks which require to retain memory relative to a sample cue for a brief period, in order to decide upon future behavioral response (e.g. [12]). M1 encodes primitive motor commands which are expressed to actions by means of SC. PPC-PFC reciprocal interaction operates in a higher level encoding WM, to develop plans regarding future actions. PFC activation is then passed to M1 which modulates its performance accordingly. Thus, the higher level orders specify the expressed actions, aiming at the accomplishment of the DR-task.

The interactions of the brain areas under discussion are modelled incrementally. The process starts by two coevolutionary processes implementing separate computational models of both M1-SC and PFC-PPC interactions. These two models are further integrated by means of another coevolutionary process operating on top of them. Both partial and composite models are embedded on a simulated mobile robot to furnish it with cognitive abilities and prove the validity of results. We employ a two wheeled robotic platform equipped with 8 uniformly distributed distance and light sensors.

Three tasks (adjusted to the needs of robotic applications) are properly specified in order to demonstrate the effectiveness of the computational procedure. The first task $T1$, accounts for primitive motion abilities without purposeful planning. For mobile robots, a task with the above characteristics is wall avoidance navigation. Since M1-SC are the brain modules which serve basic motor commands, and they are operative after lesion of the higher level structures [5], it is assumed that they are relevant for the accomplishment of wall avoidance navigation.

M1-SC interactions are modelled by means of a coevolutionary process illustrated in (Fig 4(a)). The success of wall avoidance task is evaluated by the fitness function:

$$F_1 = \left(\sum_M (sl + sr - 1) * (1.0 - p^2) \right) * \left(1 - \frac{2}{M} \left| \sum_M \frac{sl - sr}{sl * sr} \right| \right)^3 * \left(1 - 2\sqrt{\frac{B}{M}} \right)^3$$

where we assume that the robot is tested for M steps, sl, sr are the instant speeds of the left and right wheel, p is the maximum instant activation of distance sensors, and B is the total number of robot bumps. The first term seeks for

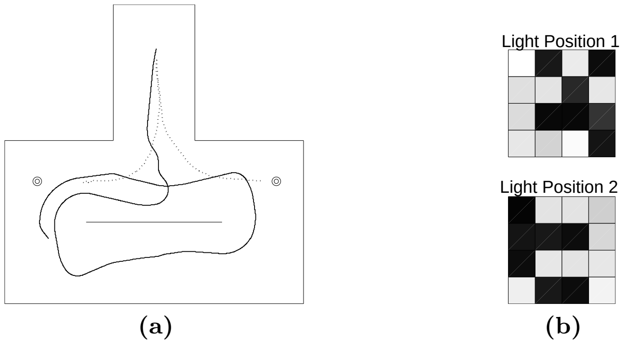

Fig. 5. Part(a) illustrates robot performance on wall avoidance navigation (solid line), and the delayed matching-to-sample task (dotted line). Targets are illustrated with double circles. Part(b) illustrates the average activation of excitatory neurons at PFC. Dark activation values indicate that the cell remain active during all the observed period, while light values indicate low activity in the same period. Evidently, each side of light cue presence is encoded by a different activation pattern.

forward movement far from the walls, the second supports straight movement without unreasonable spinning, and the last term minimizes the number of robot bumps on the walls. A sample result is illustrated in Fig 5(a).

The development of WM-like performance specifies the second task $T2$. Working memory (WM) is the ability to hold and manipulate goal-related information to guide forthcoming actions. The PFC and PPC are the brain structures most closely linked to WM [1]. Thus PPC-PFC are responsible for WM development in the proposed computational model. In the present experiment, a light cue is presented in the left or right side of the robot. WM performance aims at persistent PFC activity, related each time to the respective side of light cue.

Two different states l, r are defined, associated to the left or right side of light source appearance. For each state, separate activation-averages over the time of M simulation steps, a_j, are computed, with j identifying excitatory neurons of PFC agent. The formation of WM related to the side of light cues is evaluated by measuring the persistency of activation in PFC:

$$F_2 = \frac{1}{2}\left(\frac{v_l}{m_l} + \frac{v_r}{m_r}\right) * \min \left\{ \sum_{j, a_j^l > a_j^r} \left(a_j^l - a_j^r\right), \sum_{j, a_j^r > a_j^l} \left(a_j^r - a_j^l\right) \right\}$$

where m_l, v_l, m_r, v_r are the mean and variance of average activation at the respective states. The first term seeks for consistent PFC activation, and the second supports the development of a distinct set of active neurons for each state. A sample result is illustrated in Fig 5(b).

When the first two processes are completed, a third coevolutionary scheme commences to design the intermediate link structure which integrates the performance of the two partial models in a compound one. Following the hierarchy of motor brain areas in mammals, the memory held by PFC activation modulates M1 performance to develop goal directed motion [5, 4]. The successful interaction of substructures is demonstrated by means of a delayed response (DR) task. Specifically, a light cue is presented on the left or right side of the robot. The robot has to move at the end of a corridor memorizing the side of sample cue appearance, and then make a choice related to 90^o turn left or right, depending on the side of light cue presence.

A target location is defined in each side of the corridor depending on the position of the initial light cue (Fig 5). The robot has to approximate the target location without bumping on the walls. The successful approximation to the target location is estimated by:

$$G = \left(1 + 3.0 * \left(1 - \frac{d}{D}\right)\right)^3 * \left(1 - 2\sqrt{\frac{B}{M}}\right)^2$$

where d is the minimum euclidian distance between the target and the robot, D is the euclidian distance between the target and the starting location of the robot, and B is the total number of robot bumps. The accomplishment of $T3$ is evaluated by means of two subtasks testing separately the right or left turn of the robot for the respective positions of the light cue, employing each time the appropriate target location:

$$F_3 = G^l * G^r$$

The third hierarchical scheme performs on the results of the previous two processes evolving additionally the link agent $L5$ to support their connectivity (Fig 4(c)). The ten best individuals of $CG1$ and $CG2$ species are used as indicative partial structures to form a basis for the construction of the global model. Thus, only two species are evolved. The lower level species encoding the structure of $L5$ link agent, and $CG3$ species which choose the appropriate collaborator assembly. A sample result is illustrated in Fig 5(a).

It is easily observed that the self-organization dynamics of M1-SC structures allow the modulation of their performance according to the higher level orders. Thus, their functionality is adapted successfully from wall avoidance to goal reaching. As a result, the proposed computational framework achieves the construction of a new complex model from simple components, while the behavioral repertory of the robot is enriched.

4 Conclusions

In the present work we proposed an incremental computational framework to support brain modelling efforts. It follows an agent based approach able to simulate the distributed organization of brain areas. The employed cortical agents exhibit self-organization dynamics which serve both the experience-based learning, and the incremental modelling process by adjusting the performance of agents on circumstances with different amounts of incoming information. The employed link agents are properly formulated to connect the key sending and receiving points of cortical structures in order to achieve their integrated performance. Furthermore, the coevolutionary design approach, which matches the distributed architecture of the computational model, facilitates the integration of substructures in composite ones.

The proposed computational framework exploits the inherent ability of coevolution to integrate partial structures, exhibiting the following advantages:

– it offers a systematic methodology to facilitate incremental brain modelling process by gradually adding new coevolved species to represent brain areas,
– it supports both individual and cooperative characteristics of brain areas,
– it supports the construction of complex behaviors from simple components.

Consequently, the proposed method can potentially support large-scale brain modelling tasks and the development of competent artificial cognition mechanisms. Further work is currently underway, to investigate the suitability of our approach in large scale brain modelling tasks and the endowment of cognitive abilities to artificial organisms.

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