

Modelling Robotic Cognitive Mechanisms by Hierarchical Cooperative CoEvolution

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Abstract. The current work addresses the development of cognitive abilities in artificial organisms. In the proposed approach, neural network-based agent structures are employed to represent distinct brain areas. We introduce a Hierarchical Cooperative CoEvolutionary (HCCE) approach to design autonomous, yet collaborating agents. Thus, partial brain models consisting of many substructures can be designed. Replication of lesion studies is used as a means to increase reliability of brain model, highlighting the distinct roles of agents. The proposed approach effectively designs cooperating agents by considering the desired pre- and post- lesion performance of the model. In order to verify and assess the implemented model, the latter is embedded in a robotic platform to facilitate its behavioral capabilities.

1 Introduction

The long-term vision of developing artificial organisms with mammal-like cognitive abilities can be facilitated by computational models of the mammalian Central Nervous System (CNS). We have recently introduced a systematic method to design brain-inspired computational models of partial CNS substructures [1, 2]. The models consist of a collection of neural network agents, each one representing a CNS area. Similarly to the epigenetic life-time learning process, the performance of agents is specified by means of environmental interaction. The dynamics of epigenetic learning are designed by an evolutionary process which simulates phylogenesis, similar to [3]. Instead of using a unimodal evolutionary process we employ a cooperative coevolutionary approach which is able to highlight the specialties of brain areas and the integrated performance of substructures in the composite model [4].

In the present work, we propose a hierarchical extension of this approach, introducing a Hierarchical Cooperative CoEvolutionary (HCCE) scheme which supports the coevolution of a large number of populations. Specifically, evolutionary processes at lower levels are driven by their own dynamics to meet the special objectives of each brain area. The evolutionary process at the higher

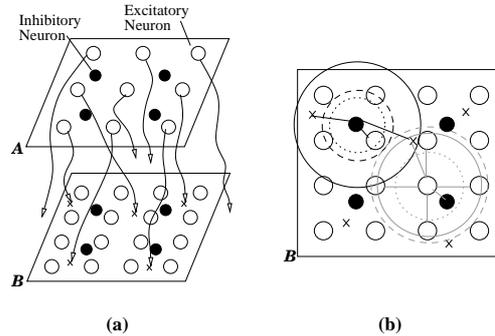


Fig. 1. Schematic representation of the computational model. Part (a) illustrates a link agent which supports information flow from cortical agent A to B. Part (b) illustrates synapse definition in cortical agent B. Neighbourhood radius for i) afferent axons is illustrated by a solid line, for ii) neighbouring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

levels, tunes lower level coevolutionary processes integrating the performance of partial components. The architecture of multiple coevolutionary processes tuned by a higher level evolution can be repeated for as many levels as necessary, forming a tree hierarchy.

Furthermore, following recent trends aiming at the study of computational models in lesion conditions [5, 6], we adapt our method to accomplish systematic modelling of biological lesion experiments. Appropriate fitness functions indicate the performance of the model when all substructures are present, and they also indicate the performance when some partial structures are eliminated. Thus, the model is able to replicate brain lesion findings.

The rest of the paper is organized as follows. In the next section, we present the structure of neural agents employed for the representation of CNS areas. In section 3 we introduce the hierarchical cooperative coevolutionary scheme which supports the design of agents. Section 4 presents the application of the proposed approach in the design of a brain-inspired computational structure. Finally, conclusions and suggestions for future work are drawn in the last section.

2 Computational Model

We implement two different neural agents, to provide a general computational framework which facilitates the modelling process: (i) a cortical agent to represent brain areas, and (ii) a link agent to support information flow.

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

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 modules 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.

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 described in [1]. 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 neighbouring neurons, or iii) inhibitory neighbouring neurons. The connectivity of neurons follows the general rule of locality. Synapse formation is based on circular neighbourhood 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).

The performance of cortical agents is adjusted by the experiences of the artificial organism obtained through environmental interaction, similar to epigenetic¹ learning [7]. To enforce experience-based subjective learning, each set of synapses is assigned a Hebbian-like learning rule defining the self-organization dynamics of the agent [8]. This is in contrast to the most common alternative of genetically-encoded synaptic strengths which prevents experience based learning. We have implemented a pool of 10 Hebbian-like rules that can be appropriately combined to produce a wide range of functionalities [1].

3 Hierarchical Cooperative CoEvolution (HCCE)

Similar to a phylogenetic process, the structure of agents can be specified by means of an evolutionary method [3]. However, using a unimodal evolutionary approach, it is not possible to explore effectively partial components, which represent brain substructures. To alleviate that, coevolutionary algorithms have been recently proposed that facilitate exploration, in problems consisting of many decomposable components [4]. Coevolutionary approaches involve separate interactive populations to design each component of the solution. These populations are evolved simultaneously, but in isolation to one another. Partial populations are usually referred as *species* in the coevolutionary literature, and thus this term will be employed henceforth.

The design of brain-inspired models fits very well to coevolutionary approaches, because separate coevolved species can be used to perform design

¹ Epigenesis here, includes all learning processes during lifetime.

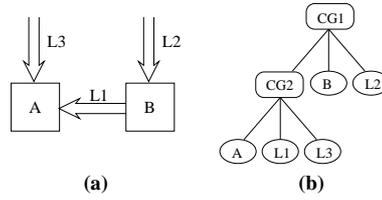


Fig. 2. Part (a) represents a hypothetical connectivity of agents. Part (b) represents the hierarchical coevolutionary scheme utilized to evolve partial structures.

decisions for each component representing a brain area. As a result, coevolution is able to highlight the special features of each brain area, and additionally the cooperation within computational modules.

We have presented a new scheme to improve the performance of cooperative coevolutionary algorithms [1, 2]. The present work extends this scheme to a hierarchical multi-level architecture, as it is described below. We employ two different kinds of species to support the coevolutionary process encoding the configurations of either a Primitive agent Structure (PS) or a Coevolved agent Group (CG). PS species specify partial elements of the model, encoding the exact structure of either cortical or link agents. A CG consists of groups of PSs with common objectives. Thus, CGs specify configurations of partial solutions by encoding assemblies of cortical and link agents. The evolution of CG modulates partly the evolutionary process of its lower level PS species to enforce their cooperative performance. A CG can also be a member of another CG. Consequently, several CGs can be organized hierarchically, with the higher levels enforcing the cooperation of the lower ones. The HCCE-based design method for brain modelling is demonstrated by means of an example (Fig 2). We assume the existence of two cortical agents connected by three link agents representing their afferent and efferent projections (Fig 2(a)). One hypothetical HCCE process employed to specify agent structure is illustrated in (Fig 2(b)).

All individuals in all species are assigned an identification number which is preserved during the coevolutionary process. The identification number is employed to form individual assemblies within different species. Each variable in the genome of a CG is joined with one lower level CG or PS species. The value of that variable can be any identification number of the individuals from the species it is joined with. PSs encode the structure of either cortical or link agents. The details of the encoding have been presented in [1, 2], and thus they are omitted here due to space limitations. A snapshot of the exemplar HCCE process described above is illustrated in (Fig 3). CGs enforce cooperation of PS structures by selecting the appropriate cooperable individuals among species.

In order to test the performance of a complete problem solution, populations are sequentially accessed starting by the higher level. The values of CG individuals at various levels are used as guides to select cooperators among PS species. Then, PS individuals are decoded to specify the structure of cortical and link agents, and the performance of the proposed overall solution is tested.

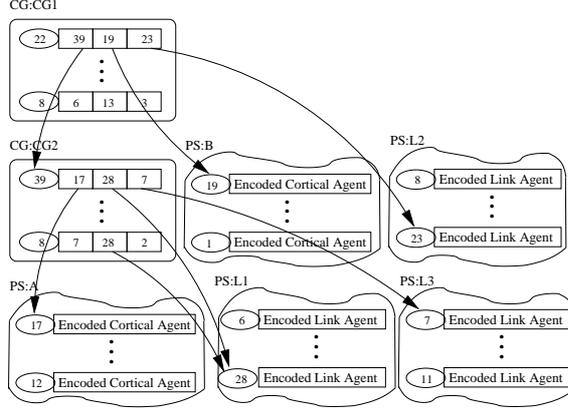


Fig. 3. A snapshot of the hierarchical coevolutionary scheme of Fig 2. Identification numbers are represented with an oval.

The proposed hierarchical scheme is able to support the simulation of lesion conditions which is a typical case for biological experiments. Specifically, by deactivating a CG together with the PS structures corresponding to its lower level species, we can easily simulate lesion of the respective brain areas. Thus, all necessary lesion conditions can be considered during the evolutionary process, and the role of each partial structure in the composite model can be highlighted.

Furthermore, our method employs separate fitness measures for different species. This matches adequately to the agent-based modelling of brain areas, because different objectives can be defined for each partial structure to preserve its autonomy. This feature of HCCE, facilitates additionally the modelling of biological lesion findings, because properly formulated fitness functions can be utilized to specify the desired pre- and post- lesion performance of the model.

For each species s , a fitness function f_s is designed to drive its evolution. All PS species strictly under a CG share a common f_s . Partial fitness functions are also utilized to evaluate the performance of the model in diverse operating conditions. Specifically, $f_{s,t}$ evaluates the ability of an individual to serve task t . The overall fitness function is estimated by:

$$f_s = \prod_t f_{s,t} \quad (1)$$

Furthermore, the cooperator selection process at the higher levels of hierarchical coevolution will probably select an individual to participate in many assemblies (e.g. the case of individual 28 of PS species L1, of Fig 3). Let us assume that an individual participates in K assemblies which means that it will get K fitness values $f_{s,t}$. Then, the ability of the individual to support the accomplishment of the t -th task is estimated by:

$$f_{s,t} = \max_k \{f_{s,t}^k\} \quad (2)$$

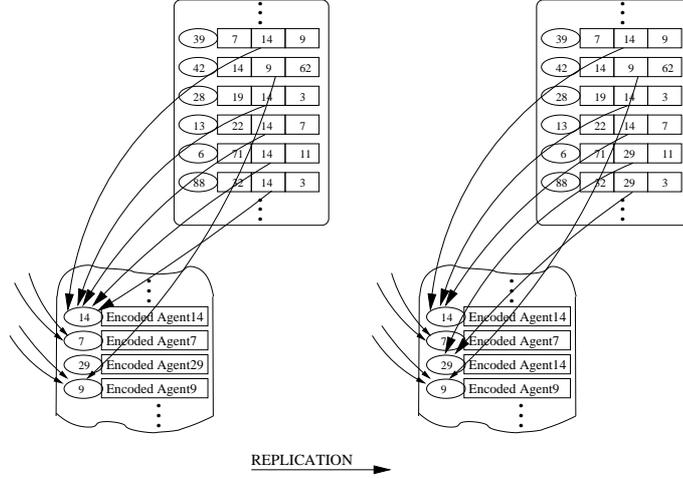


Fig. 4. Schematic representation of the replication operator ($max_c = 3$).

where $f_{s,t}^k$ is the fitness value of the k -th ($k = 1 \dots K$) solution formed with the membership of the individual under discussion.

A common problem for the coevolutionary approaches evolving assemblies of cooperators, is related to the multiple participation of some individuals in many different collaborator assemblies, while at the same time others are offered no cooperation at all. A large number of multiple cooperations is generally a drawback for the coevolutionary process, because different cooperator assemblies could demand evolution of the same individual in different directions. Non-cooperating individuals can be utilized to decrease the multiplicity of cooperations for those individuals which are heavily reused.

We have introduced a new genetic operator termed Replication (it does not aim to be a computational representative of the DNA replication), addressing the issue of multiple cooperations [1]. In short, for each unused individual x of a species, replication identifies the fittest individual y with more than max_c cooperations. The genome of y is then copied to x , and x is assigned $max_c - 1$ cooperations of y , by updating properly the CG population at the higher level. After replication, individuals x and y are allowed to evolve separately following independent evolutionary directions. This is illustrated graphically in Fig 4.

Evolutionary steps are performed separately for each species of the HCCE scheme. First, individuals are sorted according to their fitness values. Then, Replication is applied to reduce multiple cooperations. Next, 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. This process is repeated for a predefined number of evolutionary epochs.

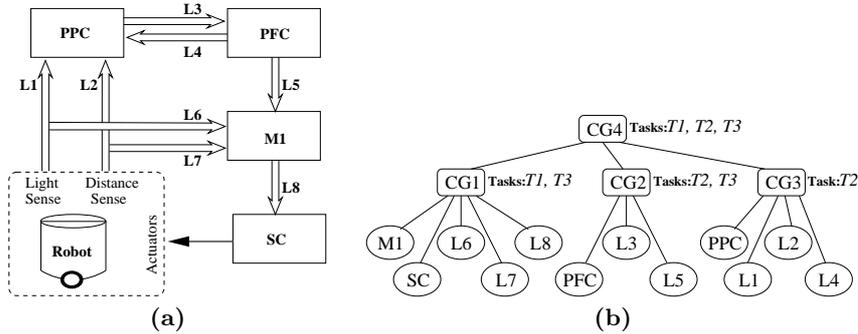


Fig. 5. (a) A schematic overview of the model. (b) A graphical illustration of the coevolutionary process.

4 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 5(a)). The organization of these areas in the mammalian brain has been extensively studied by means of delayed response (DR) tasks. 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 [9], to develop plans regarding future actions. PFC activation is then passed to M1 which modulates its performance accordingly. As a result, all the above mentioned structures cooperate for the accomplishment of a DR task by the organism. However, PFC lesion affects planning ability of the organism, resulting in purposeless motion [10].

The present work employs the hierarchical cooperative coevolutionary approach to design a model of the areas under discussion. Similar to [5, 6], the experimental process aims at reproducing a lesion scenario which is in agreement to the biological findings presented above. The composite computational model aims at the accomplishment of a DR task, developing a behavior similar to the one described in pre-lesion performance of animals [11]. This is further supported by two partial behaviors. The first accounts for the development of WM-like activation in PPC-PFC which are the brain structures most closely linked to WM [9]. The second accounts for purposeless motion by M1 when lesion occurs on the higher level structures [10]. Both partial and composite models are embedded on the robotic platform to furnish it with cognitive abilities and prove the validity of results. Specifically, we employ a two wheeled simulated robotic platform equipped with 8 uniformly distributed distance and light sensors.

Three tasks are designed to demonstrate the effectiveness of the computational procedure and also highlight the role of each agent in the model. 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. Thus, for the needs of the present study, M1-SC structures aim at wall avoidance navigation. The successful accomplishment of the task is evaluated by the function:

$$E_1 = \left(\sum_M (sl + sr - 1) * (1.0 - p^2) \right) \left(1 - \frac{2}{M} \left| \sum_M \frac{sl - sr}{sl * sr} \right| \right)^3 \left(1 - 2\sqrt{\frac{B}{M}} \right)^3 \quad (3)$$

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 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.

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. 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 presentation.

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 aiming at persistently different activation patterns in PFC:

$$E_2 = \frac{1}{2} \left(\frac{v_l}{m_l} + \frac{v_r}{m_r} \right) \cdot \min \left\{ \sum_{j, a_j^l > a_j^r} (a_j^l - a_j^r), \sum_{j, a_j^r > a_j^l} (a_j^r - a_j^l) \right\} \quad (4)$$

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 develops distinct sets of active neurons for each state.

Finally, a delayed response (DR) task $T3$, aims to combine the above behaviors formulating a complex model. 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° turn left or right, depending on the side of light cue presence. A target location is defined on each side of the corridor depending on the position of the initial light cue. The robot has to approximate the target location without crashing on the walls. The successful approximation to the target location is estimated by:

$$G = \left(1 + 3.0 * \left(1 - \frac{d}{D} \right) \right)^3 \cdot \left(1 - 2\sqrt{\frac{B}{M}} \right)^2 \quad (5)$$

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:

$$E_3 = G^l \cdot G^r \quad (6)$$

We turn now to the HCCE-based design of the model. According to the lesion experiment, each agent needs to serve more than one task, as it is illustrated in Fig 5(b). Specifically, the structures under $CG1$ are related to M1-SC interactions, and they need to serve both the wall avoidance and the delayed response task. The structures under $CG2$ are related to PFC and its afferent and efferent projections, which need to serve working memory persistent activation, and the delayed response task. The structures under $CG3$ are related to PPC and its afferent projections which have to support working memory activation only. Finally, a top level CG is employed to enforce cooperation within partial configurations aiming to support the accomplishment of all the three tasks.

The testing phase for the individuals of the coevolutionary scheme proceeds as follows. The top-level species is sequentially accessed. Each individual of $CG4$, guides cooperator selection among its lower level CG and PS species. Individuals of PS species are decoded to detailed agent structures. The composite model is tested on the accomplishment of DR task $T3$. Next, PPC-PFC interaction is isolated by deactivating the agents under $CG1$. The remaining structures are tested on working memory task $T2$. Finally, $CG1$ agents are activated back, and now $CG2$ structures are deactivated to simulate PFC lesion. The remaining agents are tested on the accomplishment of wall avoidance navigation.

The fitness functions which guide the evolution of species are designed accordingly to support the accomplishment of the respective tasks. The agent structures grouped under $CG1$ serve the success on tasks $T1$, $T3$. Following the formulation introduced in eqs. (1), (2) the fitness function employed for the evolution of $CG1$ is:

$$f_{CG1} = f_{CG1,T1} \cdot f_{CG1,T3} \quad \text{with, } f_{CG1,T1}^k = E_1, \quad f_{CG1,T3}^k = \sqrt{E_3} \quad (7)$$

where k represents each membership of an individual in a proposed solution. Similarly, $CG2$ design aims to support both the accomplishment of $T2$ and $T3$ tasks. Thus, the fitness function which guides the evolutionary process is:

$$f_{CG2} = f_{CG2,T2} \cdot f_{CG2,T3} \quad \text{with, } f_{CG2,T2}^k = E_2^2, \quad f_{CG2,T3}^k = \sqrt{E_3} \quad (8)$$

where k is as above. The third group $CG3$, consists of PPC and all link agents projecting on it. These structures need to serve only the development of working memory activation in PFC. Thus, the fitness function employed for the evolution of $CG3$ is defined by:

$$f_{CG3} = f_{CG3,T2} \quad \text{with, } f_{CG3,T2}^k = E_2 \quad (9)$$

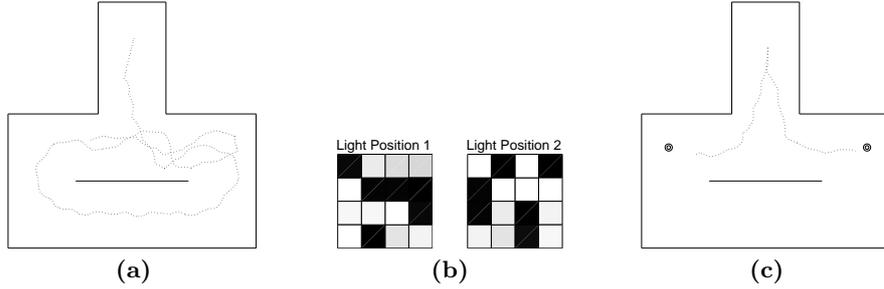


Fig. 6. (a) A sample result of robot performance, driven by M1-SC. The robot moves in a purposeless mode without bumping on the walls. (b) The average activation of excitatory neurons at PFC, for each light position. Evidently, each side of light cue presence is encoded by a different activation pattern. (c) A sample result of robot performance in the delayed match-to-sample task. Goal positions are illustrated with double circles.

where k is as above. Additionally, the top level evolutionary process $CG4$, enforce the integration of partial configurations in a composite model, aiming at the successful accomplishment of all the three tasks. Thus, the fitness function employed for the evolution of $CG4$ supports the concurrent success on wall avoidance task $T1$, working memory task $T2$, and DR task $T3$. It is defined accordingly, following the formulation introduced in eqs. (1), (2), by:

$$f_{CG4} = f_{CG4,T1} \cdot f_{CG4,T2} \cdot f_{CG4,T3} \quad \text{with,} \quad (10)$$

$$f_{CG4,T1}^k = \sqrt{E_1}, \quad f_{CG4,T2}^k = E_2^2, \quad f_{CG4,T3}^k = E_3$$

where k is as above. Following this approach, different species with separate objectives need to cooperate in order to accomplish the composite lesion scenario.

The coevolutionary process described above employed populations of 200 individuals for all PS species, 300 individuals for $CG1$, $CG2$, $CG3$, and 400 individuals for $CG4$ species. After 200 evolutionary epochs the process converged successfully. Sample results of robot performance on each task are illustrated in Fig 6. As indicated by the lesion scenario, M1-SC are able to drive the robot in a purposeless manner, following a wall avoidance policy (Fig 6(a)). At the same time, PPC-PFC interactions are able to encode the side of light cue appearance and memorize it for a brief future period (Fig 6(b)). Moreover, the composite model combines successfully the performance of partial structures to accomplish the DR task (Fig 6(c)). Consequently, the results observed by biological lesion experiments related to delayed response tasks, are successfully replicated by the model highlighting the distinct roles of substructures. It is noted that we have also approached the problem described above following an ordinary unimodal evolutionary approach, without successful outcome.

5 Conclusions

The work described in this paper, addresses the development of cognitive abilities in artificial organisms, by means of brain-inspired computational models. The proposed computational framework employs neural agent modules to represent brain areas. Additionally, a Hierarchical Cooperative CoEvolutionary (HCCE) scheme is utilized to support design specification of agent structures. This approach offers increased search abilities of partial components, and is able to emphasize both the specialty of brain areas and their cooperative performance.

The proposed HCCE scheme can also be utilized to integrate partial brain models, by introducing an appropriate number of additional higher level evolutionary processes [2]. Thus, the incremental integration of gradually more partial brain models on top of existing ones constitutes the main direction of our future work. We believe that by exploiting the proposed approach, a powerful method to design large scale reliable brain models can emerge.

Finally, it is noted that the proposed coevolutionary approach can also be utilized in contexts different from brain modelling, such as the design of cooperating robot teams, or the research on economic and social behaviors. Thus, it can be potentially employed as a general purpose method for the design of distributed complex systems.

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