Hierarchical Cooperative CoEvolution Facilitates the Redesign of Agent-Based Systems

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Abstract. The current work addresses the problem of redesigning brain-inspired artificial cognitive systems in order to gradually enrich them with advanced cognitive skills. In the proposed approach, properly formulated neural agents are employed to represent brain areas. A cooperative coevolutionary method, with the inherent ability to co-adapt substructures, supports the design of agents. Interestingly enough, the same method provides a consistent mechanism to reconfigure (if necessary) the structure of agents, facilitating follow-up modelling efforts. In the present work we demonstrate partial redesign of a brain-inspired cognitive system, in order to furnish it with learning abilities. The implemented model is successfully embedded in a simulated robotic platform which supports environmental interaction, exhibiting the ability of the improved cognitive system to adopt, in real-time, two different operating strategies.

1 Introduction

Brain-inspired computational systems are recently employed to facilitate cognitive abilities of artificial organisms. The brain of mammals consists of interconnected modules with different functionalities, implying that models with distributed architecture should be designed. In this context, a modular design approach is followed by [1,2], to develop distributed brain-like computational models.

The construction of large scale models is difficult to be accomplished by developing from scratch complicated structures. An alternative approach could be based on implementing partial models of brain areas which are gradually refined to more efficient ones. Along this line, existing approaches suffer in terms of scalability, because they lack a systematic procedure to support the progressively more complex design procedure. In contrast, they follow a manual design approach and thus they can not be used as a long-term modelling framework.

We have recently proposed a new computational framework to design distributed brain-inspired structures [3]. Specifically, the model consists of a collection of self-organized neural agents, each one representing a brain area. The performance of agents is specified in real-time according to the interaction of the composite model with the external world, simulating epigenetic learning. The

self-organization dynamics of epigenetic learning are designed by an evolutionary process which simulates phylogenesis. Following the phylogenetic/epigenetic approach, the objective adopted during the evolution of agents, is to enforce the development of brain area like performance, after a certain amount of environmental interaction. Instead of using a unimodal evolutionary process, we employ a Hierarchical Cooperative CoEvolutionary (HCCE) approach which is able to highlight the specialties of brain areas, represented by distinct agents. The agent-based coevolutionary framework has been utilized to develop models that reproduce computationally biological findings [4], and additionally to integrate partial models formulating gradually more complex ones [5].

The present study investigates the ability of the agent-based coevolutionary framework to facilitate redesign steps, enriching existing models with gradually more advanced features. The ability of partial redesign is an important characteristic for an effective and successful computational framework that aims to support long-term design processes. This is because initial design steps impose constraints to the computational structure that may harm forthcoming modelling efforts. Hence, it is necessary to have a consistent design method that reformulates systematically partial structures, and additionally guarantees the cooperation of the refined components (and potentially some completely new) with the unchanged preexisting ones.

The proposed computational framework is particularly appropriate to support redesign steps because of the distributed architecture it follows. Specifically, due to the combination of agent-based modelling with the distributed HCCE design methodology, we are able to address and specify explicitly the special features of each component in the model. As a result, when partial redesign steps are necessary, we are provided with a systematic mechanism to reconfigure subcomponents according to an enhanced set of design objectives.

The rest of the paper is organized as follows. In the next section, we present the neural agent structures used to represent brain areas, and the hierarchical cooperative coevolutionary scheme which supports the design of agents. Then, we present the results of the proposed approach on redesigning partly an artificial cognitive system in order to furnish it with reinforcement learning abilities. Finally, conclusions and suggestions for future work are drawn in the last section.

2   Method

The design of brain-inspired structures is based on the argument that the behavior of animals is a result of phylogenetic evolution, and epigenetic environmental experience [6]. Phylogenetic evolution is facilitated by the HCCE design approach, while epigenetic learning is facilitated by the self-organization dynamics of the computational model. Both of them are described below.

2.1   Computational Model

Two different neural agents provide a computational framework which supports modelling: (i) a cortical agent to represent brain areas, and (ii) a link agent to support information flow across cortical modules.
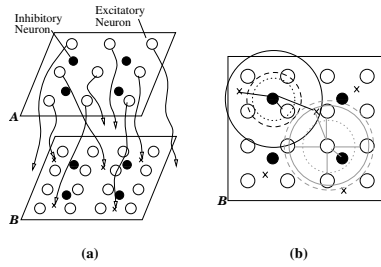
Fig. 1. Schematic representation of the computational model. Part (a) illustrates a link agent which supports information flow from cortical agent A to B. Part (b) illustrates synapse definition in cortical agent B.

Link Agent. The structure of the link agent is properly designed to support connectivity among cortical modules. Using link agents, 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 × 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. 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 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). Neighbourhood radius for i) axons is illustrated by a solid line, for ii) excitatory neurons by a dashed line, and for iii) inhibitory neurons by a dotted line. Sample neighbourhoods for excitatory neurons are illustrated with grey, while neighbourhoods for inhibitory neurons are illustrated with black.

The performance of cortical agents is adjusted by environmental interaction, similar to epigenetic[1] learning ([7]). To enforce experience-based subjective learn-

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

ing, each set of synapses is assigned a Hebbian-like learning rule defining the self-organization dynamics of the agent. 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 [3].

Reinforcement Learning. Reinforcement learning models are very popular in robotic applications in recent years. Computational models similar to the one described above have been demonstrated to exhibit reinforcement learning abilities (e.g. [8]). The idea is based on treating the reward as an ordinary signal which can be properly given as input in pre- and post- synaptic neurons to coordinate their activations. In other words, the external reinforcement signal takes advantage of the internal plasticity dynamics of the agent, in order to modulate its performance accordingly.

2.2   Hierarchical Cooperative CoEvolution

Similar to a phylogenetic process, the structure of agents can be specified by means of an evolutionary method. 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 [9]. Specifically, coevolutionary approaches involve many interactive populations to design separately 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 structures fits adequately to coevolutionary approaches, because separate coevolved species can be used to perform design decisions for each substructure 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 evolutionary scheme to improve the performance of cooperative coevolutionary algorithms, employed in the context of designing brain-inspired structures [3,4]. 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 individual 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 con-
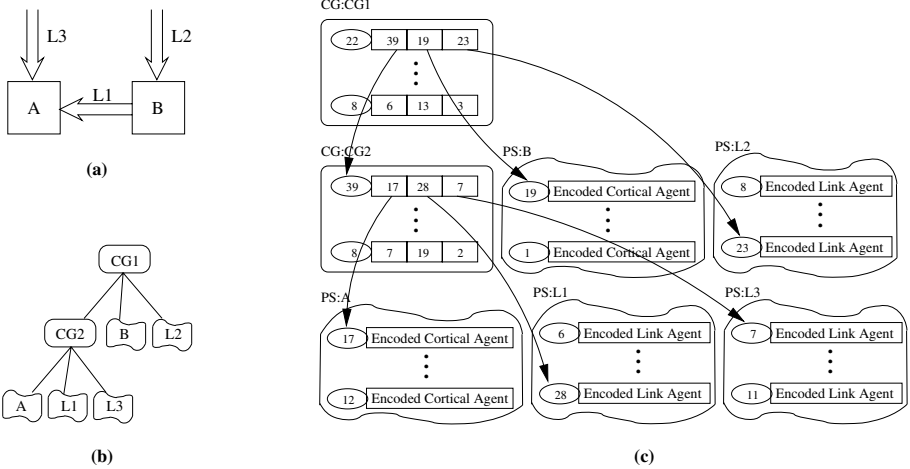
Fig. 2. An overview of the hierarchical coevolutionary scheme, with CG species tuning the evolutionary processes of PS species

nected 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)). CGs are illustrated with oval boxes, while PSs are represented by ovals.

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 [3], and thus they are omitted here due to space limitations. A snapshot of the exemplar HCCE process described above is illustrated in (Fig 2(c)). Identification numbers are represented with an oval. 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 on the desired task.

Furthermore, the proposed HCCE scheme allows the employment of separate fitness measures for different species. This matches adequately to the distributed agent-based modelling of brain areas, because different objectives can be defined for different components of the system, preserving their autonomy. As a result, the hierarchical coevolutionary scheme addresses explicitly the special roles of agents, facilitating any potential redesign of their structure.

For each species s, a fitness function f_s is designed to drive its evolution. All PS species under a CG share a common f_s. Specifically a partial fitness function $f_{s,t}$ evaluates the ability of an individual to serve task t, while the overall fitness function is estimated by:

$$f_s = \prod_t f_{s,t} \tag{1}$$

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 2(c)). 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:

$$f_{s,t} = max_k\{f_{s,t}^k\} \tag{2}$$

where $f_{s,t}^k$ is the fitness value of the k-th solution formed with the membership of the individual under discussion.

The above equations describe fitness assignment in each species of the hierarchical coevolutionary process. Just after testing the assemblies of cooperators and the assignment of their fitness values, an evolutionary step is performed independently on each species, to formulate the new generation of its individuals. This process is repeated for a predefined number of evolutionary epochs, driving each species to the accomplishment of each own objectives and additionally enforcing their composite cooperative performance.

3   Results

The present experiment demonstrates the effectiveness of the agent-based coevolutionary framework to redesign computational structures, furnishing them with gradually more advanced cognitive skills. In order to prove the validity of the result, a mobile robot is utilized to support environmental interaction. Specifically, we employ a two wheeled robotic platform equipped with 8 uniformly distributed distance, light and positive reward sensors.

In our previous work [4], we have described the utilization of the HCCE scheme to model working memory (WM) development and how it is employed to accomplish delayed response tasks. In short, a light cue is presented to the robot and the latter has to memorize the side of light cue appearance in order to make a future choice, related to 90° turning, left or right (similar tasks have been also discussed in other studies e.g. [10]). Two different response strategies can be defined. According to the Same-Side (SS) response strategy, the robot should turn left if the light cue appeared at its left side, and it should turn right if the light source appeared at its right side. Evidently, the complementary response strategy can be also defined, named Opposite-Side (OS), which implies that the robot should turn left if the light cue appeared at its right side, and it should turn right if the light source appeared at its left side.
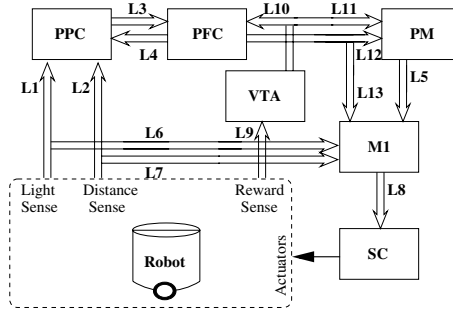
Fig. 3. A schematic demonstration of the computational model

The HCCE design mechanism has been employed to implement computational models exhibiting either the SS or the OS response strategy [4]. In both cases, the models are developed with the inborn ability to develop the correct response strategy. The question that now arises, is if we can design a single computational system that is able to adopt either the SS or the OS response strategy during life-time. The current study investigates the redesign of existing models that exhibit predefined behaviors, in order to enrich them with the ability to adapt their response strategy, as it is indicated by properly located reward signals.

3.1 Experimental Setup

The present experiment aims at extending the computational structure described in [4], thus developing an improved system with learning abilities. The composite model is illustrated in Fig 3. In order to facilitate the design procedure, we avoid designing the composite model from scratch. Particularly, the current experimental process keeps in their original formulation the components which are less involved in the learning procedure (namely, Posterior Parietal cortex (PPC), Primary Motor cortex (M1), and Spinal Cord (SC)). The biological structures mostly involved in the learning process are Prefrontal and Premotor cortices (PFC, PM) [11]. The module representing PFC was also present in our previous experiment, and it needs to be redesigned in order to be furnished with learning facilities. PM is a new module that needs to be designed from scratch. Both PFC and PM modules receive information related to the reward stimuli, adapting accordingly the motion orders to the lower levels of the motor hierarchy. Furthermore, an additional module to strengthen reward information is added, modulating effectively PFC, PM operation. This module could represent Ventral Tegmental Area (VTA) that guides learning in neocortex [12].

Learning the Opposite-Side Strategy. The training process of the robot is separated to several trials. Each trial includes two sample-response pairs, testing the memorization of two different sample cues by the robot (left or right side of light source appearance), and the selection of the appropriate delayed response in each case. Particularly, during the response phase, the light source disappears, and the robot drives freely to the end of the corridor where it has to make a

turn choice. In the OS training process, the response is considered correct, if the robot turns to opposite side of light cue appearance. In the case that the robot makes the correct choice, it drives to the reward area receiving a positive reinforcement that modulates its belief regarding the correct response strategy.

The learning of the OS response strategy is tested for T trials, each one consisting of M simulation steps. The success of the training process is evaluated by:

$$E_{tr} = \left(\sum_{T,left} \sum_{M} r \right) \left(\sum_{T,right} \sum_{M} r \right) \left(1 - \sqrt{\frac{B}{2 \cdot T \cdot M}} \right)^3 \tag{3}$$

The first term seeks for maximum reward stimuli when the correct response of the robot is considered the left side, while the second seeks for maximum reward when the correct response is the right side. The higher the reward the robot has received, the more successful was the reinforcement training process. The last term minimizes the number of robot bumps on the walls.

Additionally, HCCE facilitates the employment of partial criteria highlighting the special roles of cortical agents in the composite model. Specifically, we use a partial criterion that addresses the development of WM-like activation patterns on PFC. Two different states a, b are defined, associated with the two possible sides of light source appearance. For each state, separate activation averages, p_l, are computed, with l identifying PFC excitatory neurons. The formation of WM patterns is evaluated by:

$$E_{wm} = \left(\frac{v_a}{m_a} + \frac{v_b}{m_b} \right) \cdot \min \left\{ \sum_{\substack{l \\ p_l^a > p_l^b}} \left(p_l^a - p_l^b \right), \sum_{\substack{l \\ p_l^b > p_l^a}} \left(p_l^b - p_l^a \right) \right\} \tag{4}$$

m_a, v_a, m_b, v_b are the means and variances of average activation at states a, b. The first term enforces consistent activation, while the second supports the development of separate activation patterns for each state a, b.

Another criterion addresses the development of different activation patterns in PM structure. They are related to the different higher level motion commands that should be passed to M1. Two different states r, l are defined, associated with the commands of right or left turning. For each state, separate activation averages, p_k, are computed, with k identifying PM excitatory neurons. The successful development of distinct activation patterns for the right and left turning is measured by:

$$E_c = \left(\frac{v_r}{m_r} + \frac{v_l}{m_l} \right) \cdot \min \left\{ \sum_{\substack{k \\ p_k^r > p_k^l}} \left(p_k^r - p_k^l \right), \sum_{\substack{k \\ p_k^l > p_k^r}} \left(p_k^l - p_k^r \right) \right\} \tag{5}$$

The explanation of the measure is similar to eq (4).

Finally, an additional criterion highlights the development of different patterns on the VTA structure, related to the two possible locations of the reward signal. Two different states x, y are defined, associated with the right or left reward
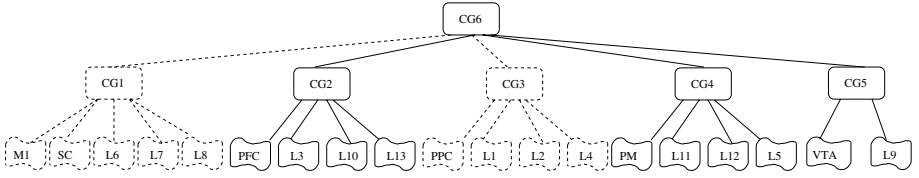
Fig. 4. An overview of the extended Hierarchical Cooperative CoEvolutionary process employed to design the composite computational model

location. For each state, separate activation averages, p_t, are computed, with t identifying VTA neurons. This is described by:

$$E_r = \left(\frac{v_x}{m_x} + \frac{v_y}{m_y} \right) \cdot \min \left\{ \sum_{\substack{t \\ p_t^x > p_t^y}} (p_t^x - p_t^y), \sum_{\substack{t \\ p_t^y > p_t^x}} (p_t^y - p_t^x) \right\} \tag{6}$$

The explanation of the measure is similar to eq (4).

Learning the Same-Side Strategy. Just after testing the performance of the robot on learning the OS strategy, the computational structure is re-initialized, and we test if it is able to adopt the SS response strategy, by means of a different set of reward stimuli. The process is again separated to T trials, and it is very similar to the one described for OS training. Specifically, each trial includes two sample-response pairs, but this time, due to the SS strategy the reward stimulus is located to the same side that the light cue appeared.

The measure evaluating the adoption of the SS strategy by the robot is the same with the one described in eq. (3). Furthermore, additional evaluation measures similar to those described in eqs (4), (5), (6) highlight the roles of PFC, PM, AmpR structures in the composite model. Overall, we employ two different sets of measures, namely $E_{wm,os}$, $E_{c,os}$, $E_{r,os}$, $E_{tr,os}$ and $E_{wm,ss}$, $E_{c,ss}$, $E_{r,ss}$, $E_{tr,ss}$ evaluating the ability of the robot to adopt either the OS or the SS strategy during the reward-based training process, and the distinct role of substructures in the composite model.

3.2   Computational Modelling

We turn now to the design of the model by means of the HCCE scheme. The hierarchical coevolutionary process that re-designs and extends the computational model is illustrated in Fig 4. The species below CG1 and CG3 are depicted with a dotted line, in order to demonstrate that we keep their original structure (formulated in our previous experiment [4]) and they are not evolved in the current coevolutionary design procedure. According to the experimental scenario followed in the present study, two behavioral tasks $t1$, $t2$, are employed to validate respectively the adoption of either the OS or SS response strategies.

Specifically, the fitness function employed for the evolution of $CG2$ and its lower level species, evaluates the success of OS and SS learning procedures, and

the development of WM activity in PFC. Following the formulation introduced in eqs. (1), (2), this is described mathematically by:

$$f_{CG2} = f_{CG2,t1} \cdot f_{CG2,t2} \quad \text{with} \quad f^k_{CG2,t1} = E_{wm,os} \cdot E_{tr,os}, \quad f^k_{CG2,t2} = E_{wm,ss} \cdot E_{tr,ss} \quad (7)$$

where k represents each membership of an individual in a proposed solution.

The agent structures grouped under $CG4$ serve the success on OS, SS learning, and the development of the appropriate higher level motion commands on PM. Thus, the fitness function employed for the evolution of $CG4$ is:

$$f_{CG4} = f_{CG4,t1} \cdot f_{CG4,t2} \quad \text{with} \quad f^k_{CG4,t1} = E_{c,os} \cdot E_{tr,os}, \quad f^k_{CG4,t2} = E_{c,ss} \cdot E_{tr,ss} \quad (8)$$

where k is as above.

The agent structures grouped under $CG5$ support OS, SS learning and the development of different reward patterns on VTA. Thus, the fitness function employed for the evolution of $CG5$ is:

$$f_{CG5} = f_{CG5,t1} \cdot f_{CG5,t2} \quad \text{with} \quad f^k_{CG5,t1} = E_{r,os} \cdot E_{tr,os}, \quad f^k_{CG5,t2} = E_{r,ss} \cdot E_{tr,ss} \quad (9)$$

where k is as above.

Finally, the top level CG enforces the integration of partial configurations in a composite model, aiming at the cooperation of substructures in order to facilitate the accomplishment of both learning processes, and additionally highlighting the role of each cortical agent in the composite model. The fitness function employed for the evolution of $CG6$ is defined accordingly, by:

$$f_{CG6} = f_{CG6,t1} \cdot f_{CG6,t2} \quad \text{with} \quad \begin{aligned} f^k_{CG6,t1} &= E_{tr,os} \cdot \sqrt{E_{wm,os} \cdot E_{c,os} \cdot E_{r,os}}, \\ f^k_{CG6,t2} &= E_{tr,ss} \cdot \sqrt{E_{wm,ss} \cdot E_{c,ss} \cdot E_{r,ss}} \end{aligned} \quad (10)$$

where k is as above.

The hierarchical coevolutionary process described above, employed populations of 200 individuals for all PS species, 300 individuals for $CG2$, $CG4$, $CG5$, and 400 individuals for $CG6$. After 70 evolutionary epochs the process converged successfully. Sample results of robot learning to adopt the OS and SS strategies are illustrated in Figs 5, 6. In both cases, the response of the robot in the first two trials (columns 2,3) are incorrect. However, in the third trial (column 4), the robot tries another strategy which is successful, and it is continued for all the remaining trials. As a result, HCCE successfully redesigns the computational structure, formulating an improved model with reinforcement learning abilities.

Overall, the present experimental procedure demonstrates the power of the HCCE-based design mechanism to refine an existing computational structure in order to enhance its functionality. The same results demonstrate also that the distributed design mechanism is particularly appropriate to enforce the cooperation among new and preexisting components. As a result, HCCE can be consistently employed to facilitate the success of complex, long-term design procedures.
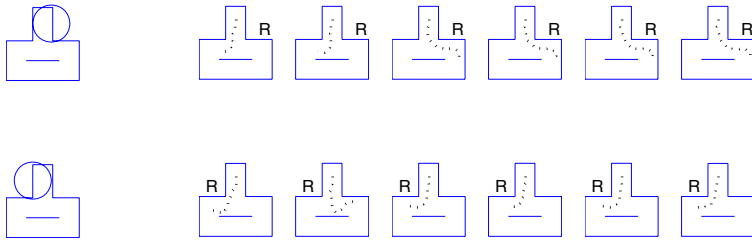
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Fig. 5. A sample result of robot performance in the Same-Side response task. The first column illustrates sample cues. The rest columns (2-7) demonstrate the response of the robot in consecutive trials. The "R" depicts the side of the reward. Snapshots in the first line illustrate robot responses when light sample cue appears to the right, while the second line illustrates robot responses when light sample appears to the left.
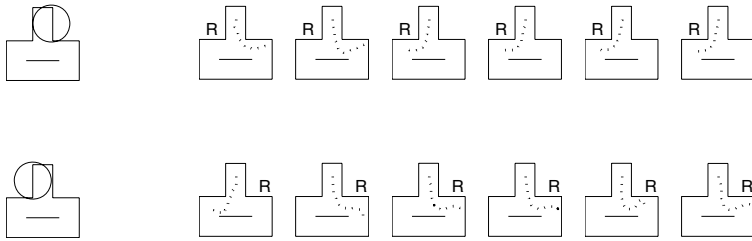

Fig. 6. A sample result of robot performance in the Opposite-Side response task. The first column illustrates sample cues. The rest columns (2-7) demonstrate the response of the robot in consecutive trials. The "R" depicts the side of the reward. Snapshots in the first line illustrate robot responses when light sample cue appears to the right, while the second line illustrates robot responses when light sample appears to the left.

4   Conclusions

The work described in this paper, addresses the development of cognitive abilities in artificial organisms by means of implementing brain-inspired models. Specifically, we introduce a systematic computational framework for the design and implementation of brain-like structures. This is based on the employment of neural agent modules to represent brain areas, and an HCCE-based design methodology to facilitate both the design of partial models and their further advancement in gradually more complex ones.

Due to the distributed architecture followed by both the agent-based model and the HCCE design methodology, the proposed computational framework is able to address explicitly the structure of system components. Hence it is able to add new components in the model, and re-design some of the pre-existing ones in order to advance gradually the capabilities of the model.

We believe that by exploiting the proposed approach, a powerful method to design brain-inspired structures can emerge. Further work is currently underway to investigate the suitability of our approach in large scale modelling tasks.

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